Essays on the Effects of Health Insurer and Health Care Provider Organization on Patient Treatments

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Abstract

The United States health care system has garnered significant policy attention in recent years. The importance of the health care system is in part a fiscal concern, but also because of the role it plays in peoples' lives. In many cases, patients' lives greatly depend on the quality of the health care they receive. The organization of the health care system has undergone many dramatic changes in recent years and it is important to understand how these changes impacted the way the health care system functions. The effects of the various changes on health care spending and, in particular, on patient treatment outcomes remain poorly understood. In this dissertation, I investigate how three recent trends in the organization of the U.S. health care system have impacted the treatments that patients receive: the decrease in health insurer competition, the increase in hospital-physician integration, and the use of managed care in public insurance programs.

In Chapter 1, I study whether health insurer competition increases the use of costly treatments. Health insurers have an incentive to influence health care providers' treatment decisions to reduce their own reimbursement costs. If a single insurer is effective at inducing a provider to use less costly treatments, the provider may do so for patients of other insurers. While an insurer can reduce their own costs, spillover of their cost reduction can allow rival insurers to also benefit. I develop a theoretical framework demonstrating how competition can deter insurers from limiting costly treatments due to provider-level spillover concerns. I empirically test the relationship between Health Maintenance Organization (HMO) competition and Cesarean section (C-section) use. C-sections are a costly treatment that HMOs have an incentive and the potential ability to influence. I argue that HMOs' return to limiting C-sections should be lower at hospitals that contract with more HMOs due to potential spillover. I find that patients are more likely to receive C-sections at hospitals with lower HMO concentration - where spillover poses a greater deterrent to HMO cost reduction. The magnitude of this effect increases with the level of HMO competition in the market containing the hospital. Taken together, these results provide evidence that HMO competition can increase the use of C-sections at hospitals that contract with multiple HMOs.

In Chapter 2, I study whether hospital-physician integration affects health care utilization by altering the treatments patient receive. I estimate the effect of hospital-physician integration on the use of C-sections in childbirth using a sample of privately insured patients from California over 2005-2012. Childbirth is a convenient treatment setting to study utilization because it presents a binary choice between a high intensity, high cost procedure (C-section) and a comparatively low intensity, low cost alternative (vaginal birth). I am able to decompose the effect of hospital-physician integration on C-section use by the form of integration. I exploit heterogeneity in the various forms hospital-physician integration to investigate whether particular characteristics of integration affect C-sections use. This allows me to consider mechanisms suggested by previous literature through which integration potentially affects C-section use. I find that C-sections are 2% less likely at integrated hospitals than at hospitals with no physician affiliations. The negative effect of hospital-physician integration on C-section use is consistent across forms of integration where hospitals contract with physician practices and forms where hospitals own physician practices.

In Chapter 3, I study whether shifting Medicaid beneficiaries from Fee-for-Service (FFS) to Medicaid managed care (MMC) affects the treatments that they receive. I perform a case study of the effect of two California counties switching their Medicaid beneficiaries from FFS to MMC in October of 2009 on the use of C-sections in childbirth for their beneficiaries. I use hospital discharge data from California over 2006-2012 to estimate the "intent-to-treat" effect of counties switching from FFS to MMC on the likelihood that their beneficiaries receive C-sections. I find that switching from FFS to MMC is associated with an 11.9% increase in C-sections.

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Contents

Chapter 1

Does Health Insurer Competition Increase the Use of Costly Treatments?

The majority of the U.S. population relies on private health insurance to cover their medical expenses.[1] Recently, private health insurers have been consolidating making insurance markets less competitive. By 2014, health insurance markets in over 80 percent of states were categorized as highly concentrated by the Federal Trade Commission and Department of Justice horizontal merger guidelines.[2] A growing policy concern is whether this consolidation warrants regulatory action. In 2017, the Department of Justice blocked Aetna's proposed $37 billion merger with Humana, and blocked Anthem's proposed $48 billion merger with Cigna (de la Merced and Picker, 2017). The primary argument in favor of regulation is that competitive insurance markets benefit consumers by promoting lower premiums. A counter argument is that insurer competition may reduce efficiency by stifling insurers from innovating to reduce costs. If this were the case, increased costs would offset insurers' ability

[1]As of 2014, 54% of the US population and 67.3% of adults under the age of 65 had private health insurance (Kaiser Family Foundation, 2016a; National Center for Health Statistics, 2014).

[2]88% of states had highly concentrated large group health insurance markets and 82% of states had highly concentrated small group markets (Kaiser Family Foundation, 2016b; Kaiser Family Foundation, 2016c). A market is considered highly concentrated by the horizontal merger guidelines if it has a Herfindahl-Hirschman Index greater than 2,500 - on a 0 to 10,000 scale (DOJ and FTC, 2010).

to lower premiums - the primary benefit to competition. However, there is little empirical evidence supporting this counter argument to date (Dafny, 2015).

I ask whether insurer competition can undermine insurers' incentive to reduce costs. In the U.S. health care system, patients receive care from health care providers (hospitals and physicians) who are reimbursed by the patients' insurers. Insurers have an incentive to contain spending by influencing providers to perform low cost treatments. Providers, who principally determine treatments, have incentives to perform costly treatments: direct financial incentives (i.e., higher reimbursements paid for more costly treatments); concerns about malpractice lawsuits for under-provision of care. To combat this problem, private insurers use both financial and non-financial incentives to encourage contracted providers to internalize cost concerns (Gaynor et al., 2004). A complication is that providers typically treat patients from multiple insurers. Moreover, providers tend to treat patients of different insurers similarly because doing otherwise would be either unethical or inconvenient (Spetz et al., 2001). Thus, if a single insurer is effective at inducing a provider to use less costly treatments, the provider likely does so for patients of all insurers (Hellinger, 1996; Maeng et al., 2010). While an insurer can reduce their own costs, spillover of their cost reduction can allow other insurers to also benefit (Beaulieu et al., 2006; Chernew et al., 2004, Maeng et al., 2010). The degree to which this "spillover" of insurer cost reduction affects whether insurers invest in cost reduction depends on the extent to which insurers care about reducing their rivals' costs. Competition potentially causes insurers' profits to be adversely affected by lowering their rivals' costs. Therefore, competition can cause spillover to deter insurers from investing in cost reduction to discourage providers from using costly treatments. If this were the case, insurer competition could increase the use of costly treatments.

I study the effect of insurer competition on the use of Cesarean sections (C-section) in childbirth. Childbirth is a relevant clinical setting because it presents providers with a binary decision between a high cost treatment (C-sections) and a comparatively low cost alternative (vaginal birth). Providers have financial, time, and malpractice incentives to perform C-sections (Gruber and Owings, 1996). In many cases, the medical necessity of a C-section is difficult to judge, which allows providers flexibility to favor their own incentives over insurer cost concerns (Foo et al., 2017; Keirns, 2015). As a result, there is a large body of literature that documents how

C-section use responds to a variety of provider financial and legal incentives. Also, the U.S. Department of Health and Human Services is currently advocating for a reduction in nationwide C-section rates (Kozhimannil et al., 2013). C-sections are a treatment that insurers have strong cause to limit, should respond to changes in provider incentives, and a treatment with clear implications for health care costs.

I develop a theoretical framework to formalize the intuition about how insurer competition affects C-section use and to guide my subsequent empirical analysis. Insurers sell an insurance plan in a market and contract with a single hospital. Insurers reimburse the hospital for treatments received by their patients. The hospital chooses to perform either a vaginal birth (low cost to the insurer) or a C-section (high cost) and the patients follow the hospital's recommendations. Insurers can invest to encourage the hospital to perform vaginal births. However, a single insurer's investment may also result in the hospital performing fewer C-sections for their rival insurers' patients - lowering their rivals' costs. Because insurers compete for enrollees through the premiums that they charge, if an insurer lowers their rivals' costs, the other insurers can in turn reduce their premiums to capture demand. Competition creates a mechanism through which spillover reduces the investing insurer's return on their investment. This framework yields two predictions. First, spillover has a larger, negative effect on insurers' return on investment if there are more insurers contracting with the hospital. Second, the level of competition between insurers in the market magnifies this effect. If a market is more competitive - i.e., an individual insurer's demand is more responsive to other insurers' premiums - insurers are more responsive to the investment deterrent created by spillover. Competition can therefore inhibit insurers from limiting C-sections and increase the number of C-sections performed.

The predictions of the model motivate two empirical questions: 1) Are C-sections more likely at hospitals that contract with more insurers? 2) Is this effect larger at hospitals located in more competitive insurer markets? I limit my empirical analysis to focus on Health Maintenance Organizations (HMOs). I use the concentration of HMOs within hospitals to measure of the number of HMOs contracting with hospitals. At less concentrated hospitals, discharges are spread across more HMOs. I approximate the level of competition between HMOs in a market using the concentration of HMO plans at the market level; HMOs should be less competitive in more concentrated markets. Using these empirical measures, I can rephrase the two empirical questions: 1) Are C-sections more likely at hospitals with lower HMO concentration (more HMOs)? 2) Is this effect larger at hospitals located in less concentrated (more competitive) HMO markets?

To answer these questions, I use hospital discharge data from the California Office of Statewide Health Planning and Development (OSHPD) over 2005-2013. These data contain all discharges from California hospitals over the sample time period. The critical feature of the OSHPD data is information on HMO patients' insurance plans, which I use to construct the measures of HMO concentration at the hospital and market level. The data also include patient demographic, diagnostic, and treatment information. I measure HMO concentration at the hospital level and the market level using the Herfindahl-Hirschman Index (HHI).[3] I define the geographic HMO market containing each hospital as the Health Insurance Rating Area in which a hospital is located.

I estimate a linear probability model where the likelihood that a patient receives a C-section depends on both hospital level HHI and the interaction of hospital and market level HHI. This specification allows me to answer my empirical questions by estimating how the effect of hospital level HHI on C-sections varies with market level HHI. However, these estimates may be biased due to the endogeneity of hospital and market level HHI. In particular, unobservable hospital, HMO, market, and physician characteristics may be correlated with hospital and market level HMO concentration, as well as patients' likelihood of receiving C-sections. For example, if a hospital preferred performing vaginal births to C-sections all else equal, the hospital would have a low C-section rate. HMOs may be more inclined to contract with this hospital, resulting in a lower concentration of HMOs at this hospital. To account for such potential endogeneity, I estimate my empirical model using two stage least squares (2SLS). The instrumental variables I use are geographic characteristics of a hospital's county and market correlated with hospital and market level HHI, respectively. The identifying assumption is that these geographic characteristics are uncorrelated with a patient's likelihood of receiving a C-section, conditional on observable patient, hospital and HMO characteristics.

[3]For notational simplicity, from this point forward I refer to the HHI of HMOs at the hospital level as "hospital level HHI." I refer to the HHI of HMOs at the market level as "market level HHI."

Answering my first empirical question, I find that more C-sections are performed at hospitals with lower HMO concentration. At an average hospital in an average market, a 10 percent decrease in hospital level HHI results in a 4.2 percent increase in the likelihood of receiving a C-section. This result implies that if a hospital contracts with more HMOs (lowering the concentration of HMOs at the hospital), then the hospital is predicted to perform more C-sections. The negative association between hospital level HMO concentration and C-section use supports the theoretical prediction that spillover represents a greater deterrent to HMOs limiting C-sections at hospitals that contract with more HMOs.

Answering my second empirical question, I find that the effect of hospital level HHI on C-section use is larger at hospitals located in more competitive (less concentrated) HMO markets. At an average hospital, a 10 percent decrease in hospital level HHI increases C-section likelihood by 3.0 percent if the hospital is located in a less competitive market (25^{th} percentile of insurer HHI) compared to 5.9 percent if the hospital is located in a more competitive market (75^{th} percentile of insurer HHI). The level of HMO competition in a market determines the size of the effect of hospital level HHI on C-section likelihood. It follows that for a given level of hospital level HMO concentration, if the level of HMO competition in the market containing the hospital increases then the number of C-sections performed at the hospital is predicted to increase. Therefore, HMO competition can increase the use of C-sections at hospitals that contract with multiple HMOs.

My results support the mechanism highlighted in my theoretical framework: competition can deter HMOs from limiting C-sections at hospitals due to spillover concerns. However, this interpretation is dependent on two assumptions. First, I assume that insurer cost reduction spillover occurs. The predictions from my theoretical model, and subsequent empirical analysis, depend on this assumption. To justify this assumption, I provide evidence that an individual HMO (the largest HMO at each hospital) is able to influence whether their patients receive C-sections. I then show that patients of other insurers within the same hospital are similarly affected; I provide evidence that patients of other insurers within the same hospital are affected by spillover. Second, I interpret the negative relationship between hospital level HMO concentration and C-section use as evidence of HMOs altering whether they discourage hospitals from performing C-sections due to spillover concerns. To address this concern, I consider three main alternative explanations for the negative relationship between hospital level HMO concentration and C-section use suggested by previous literature. In each case, I provide evidence that my results are inconsistent with these alternative explanations. In particular, I argue that these mechanisms cannot explain why hospital level HHI has a larger, negative effect on C-section use at hospitals located in more competitive HMO markets.

I contribute to the literature by providing empirical evidence that insurer competition can increase the use of a specific, costly treatment (C-sections). While more work is necessary to investigate whether insurer competition similarly affects other treatments, the implication of my results is that insurer competition can increase insurer costs. Previous literature generally supports the canonical economic logic that competition benefits consumers by reducing premiums (Dafny et al., 2012; Ho and Lee, 2017; Trish and Herring, 2015; Wholey et al., 1995). However, Ho and Lee (2017) also show that insurer competition's negative effect on premiums can theoretically be offset by raising insurer costs through reducing their ability to negotiate low reimbursement prices with providers. I complement this work by providing empirical evidence of an additional channel through which insurer competition can increase insurer costs. Both this study and Ho and Lee (2017) highlight mechanisms of how complicated health insurer - health care provider relationships can potentially confound the implications of insurer competition. Consequently, it is important to consider the structure of both health insurer and health care provider markets when trying to assess whether insurer competition will benefit consumers or lower health care spending.

1.1 Background

1.1.1 Health Insurers and Provider Treatment Decisions

The structure of the U.S. health care industry places insurers in a position where it is in their best interest to influence which treatments providers perform. Private health insurers compete with each other over premiums, benefit structure, and quality of provider networks. Insurers contract with health care providers (both hospitals and physicians) to allow patients to visit providers, and to determine what insurers will reimburse on behalf of their patients. Once an insurer's contracts with providers are in place, reimbursement costs make up the majority of the insurer's costs (Thorpe, 1992). Insurers' reimbursement costs are then determined by which treatments providers choose to perform.

Providers face a variety of incentives to perform high cost treatments. Reimbursements create a direct financial incentive for providers to perform high cost treatments. In many cases, the total reimbursement bill a patient's insurer must pay a particular provider increases with the quantity and quality of services the provider performs.[4] Provider competition also creates incentive to perform high cost treatments. Providers compete with each other to attract patients through, among other things, quality of care. By offering higher quality (and higher cost) treatments, providers can improve patient demand by raising patients' perceived quality. If patient demand for an individual provider is high, the provider can command higher reimbursement prices from insurers and therefore earn higher profits. The fear of malpractice lawsuits is another incentive to perform high cost treatments. Providers may engage in "defensive medicine" - prescribing (potentially) excessive treatments to reduce their risk of being sued for medical malpractice (Kessler, 2011). The information asymmetry between providers and insurers compounds providers' various incentives to perform costly treatments. Providers can directly observe patient symptoms where insurers observe ex-post diagnosis and treatment decisions. This asymmetry allows providers

[4]This is especially true for insurers who reimburse providers by Fee-For-Service (FFS) payments where insurers reimburse providers a negotiated fee for each treatment providers perform. However, insurers may use other types of payment schemes to mitigate this problem, such as paying a fixed ammount for patients with certain conditions.

to favor their own incentives (relative to insurers' cost concerns) when deciding treatments.

Insurers, therefore, have an incentive to limit their reimbursement costs by influencing provider treatment decisions. In this study, I focus on private insurers, specifically Health Maintenance Organizations (HMOs).[5] To reduce costs, nearly all HMOs invest in both financial and non-financial incentives to encourage providers to internalize cost concerns (Gaynor et al., 2004). Some examples of financial incentives to providers include the insurer reimbursing a fixed amount for all services performed by providers (capitation) and making bonus payments to providers conditional on the providers achieving spending goals (Baker, 2003; Bundorf et al., 2004; Gaynor et al., 2004). Alternatively, HMOs can also provide treatment guidelines and review physician practice patterns to manage utilization of medical services with the implicit threat that HMOs can exclude physicians or hospitals from their provider networks (Baker, 2003; Bundorf et al., 2004; Ma and McGuire, 2002).

1.1.2 Spillover of Insurer Incentives to Providers

Insurers' incentives to influence provider treatment decisions are complicated when providers contracts with multiple insurers. Providers typically hold contracts with multiple insurers.[6] According to the American Hospital Association's annual survey, from 2003-2012 the median hospital nationwide held six HMO contracts (conditional on holding one). Though providers may treat patients from multiple insurers, patients from the different insurers are not necessarily treated differently. In particular, it may be either unethical or inconvenient for providers to treat patients differentially based on their insurer (Spetz et al., 2001). For this reason, providers tend to treat patients

[5]I generally study insurers' ability to influence provider behavior. Becauses HMOs tightly control which providers patients visit, they have more ability than other types of insurers to influence provider behavior (Chernew et al., 2004; Ma and McGuire, 2002). For this reason, HMOs are the most relevant type of insurance plan for this analysis, and throughout the chapter I use the terms insurer and HMO interchangebly.

[6]Insurers compete for enrollees through, among other dimensions, the strength of their provider networks. Insurers can attract patients by contracting with a greater number of providers within markets. In some cases, this causes insurers to try to contract with the majority of providers in a market (Haas-Wilson, 2003).

of different insurers similarly.[7]

When an insurer influences a provider's treatment style, the insurer may therefore affect the way the provider treats other insurers' patients. For example, if an insurer is successful at inducing a provider to perform fewer costly treatments for the insurer's own patients, the provider may also perform fewer costly treatments for all insurers' patients (Baker, 2003; Bundorf et al., 2004; Chernew et al., 2004; Hellinger, 1996). I refer to one insurer's ability to influence the way a provider treats other insurers' patients as "spillover." Baker (2003) argues that the literature produces a "consensus" that managed care plans (i.e., HMOs) can cause health system wide changes due to the spillover of managed care cost reduction. Bundorf et al. (2004) find that Medicare patients are treated in a more cost conscious manner in areas with higher HMO penetration due to such spillover of HMO induced changes to provider practice style.[8] A consequence of spillover is that if an insurer tries to reduce their own cost at a provider, she may simultaneously reduce the cost of other insurers who contract with that provider.

1.1.3 Insurer Competition and Spillover Concerns

Insurers have an incentive to limit their reimbursement costs by influencing provider treatment decisions. However, if an insurer encourages a provider to reduce costs then she may also reduce the costs for other insurers who contract with that same provider. On its own, spillover of insurer cost reduction creates a positive externality. For example, Bundorf et al. (2004) provide evidence that Medicare is able to enjoy cost reductions due to the efforts of HMOs. Spillover's impact on an insurer's decision to influence a provider's treatment decisions depends on how concerned the insurer is about reducing their rivals' costs. Competition can cause insurers' profits to be adversely affected by lowering their rivals' cost. Insurers' ability to compete with their rivals on premiums and plan quality is determined by their costs relative to their rivals'. Competition can therefore cause insurers to limit their cost reduction

[7]Cutler et al. (2013) find that the main determinant of geographic variation in medical spending and care utilization is provider (physician) beliefs about treatment options (their practice style).

[8]Bundorf et al. (2004) specifically argue that their results show that spillover from HMO induced cost reductions is the reason that Medicare FFS patients with Acute Myocardial Infarction are less likely to receive costly procedures.

because they cannot privately capture the benefits of their cost reduction at providers who contract with many insurers (Chernew et al., 2004; Maeng et al., 2010). If insurer competition causes spillover to deter insurers from discouraging providers from performing costly treatments, competition can increase the use of costly treatments.

While there is a small body of literature that argues spillover could inhibit insurers from investing in cost reduction and quality improvement, there is little empirical evidence to date. Maeng et al. (2010) find that when multiple insurers contract with the same physicians, insurers' quality scores converge to lower levels. The mechanism, they hypothesize, is that spillover concerns make insurers wary of investing in quality improvement when their provider network overlaps with other insurers. Beaulieu et al. (2006) argue spillover concerns could explain why diabetes management programs are not more prominent. In this study, I extend these arguments by showing how insurer competition can create a mechanism through which spillover affects insurer investment in cost reduction.

1.1.4 Treatment Context: Cesarean Sections

To test if competition affects whether insurers influence provider treatment decisions, I study the effect of health insurer competition on the use of Cesarean sections (C-sections) in childbirth. C-sections are a treatment that insurers have an incentive to influence. In many cases, childbirth presents a binary decision between a high cost procedure (C-section) and a comparatively low cost procedure (vaginal birth). The Truven Market Scan Study (2013) found that commercial insurers' average total payment for maternal and newborn care was $27,866 for patients with Cesarean delivery compared to $18,329 for vaginal delivery.

Insurers have an incentive to encourage providers to substitute vaginal births for C-sections when possible because C-sections are more costly for insurers to reimburse and because provider incentives generally favor performing C-sections.[9] In addition

[9] In this section, I refer to both hospitals and physicians as providers. Typically, physicians make treatment decisions. It is also possible that hospitals and physicians may have different incentives to favor different treatments. Ultimately, I am only able to observe treatments at the hospital level, rather than at the physician level. Throughout the duration of my analysis I treat hospitals and physicians as a unit (providers). I discuss the associated empirical challenges of treating hospitals and physicians as a single entity in Section 1.4.1.

to this direct financial incentive for providers to perform C-sections over vaginal births, C-sections can be more efficient for providers to perform because they can be scheduled prior to delivery and completed in less time (Gruber and Owings, 1996; Johnson and Rehavi, 2016). Providers also may favor C-sections over vaginal births to lower their risk of malpractice lawsuits (Gruber and Owings, 1996; Yang et al., 2009). Providers' decisions to perform unscheduled C-sections are often due to prolonged labor, a distinction that can be subjective (Keirns, 2015). Insurers are frequently not able to accurately judge the medical justifications for or against a C-section (Foo et al., 2017). The information asymmetry between providers, who perform the procedures, and insurers, who observe diagnoses ex-post, allows providers discretion in deciding treatments; providers have both the incentive and ability to over perform C-sections. For this reason, there is a large body of evidence that C-section use responds to a variety of provider financial and legal incentives.[10]

C-sections are treatment with clear implications for health care costs and patient welfare. C-sections are the most frequently performed inpatient procedure in the United States (Kozhimannil et al., 2013). While in some cases C-sections are a life saving procedure for both mothers and infants, they also come with significant fiscal and health consequences. The prevalence of C-sections has not noticeably improved public health outcomes and is indicative of overuse.[11] Childbirth accounts for nearly $50 billion annually. C-sections are a growing component of these costs because they command higher reimbursement prices than vaginal births and also a greater share of hospital resources. Because C-sections are an intensive surgical procedure, they frequently necessitate longer lengths of stay, have higher risks of complications, and higher re-hospitalization rates than vaginal births.[12] C-sections are also associated

[10] Alexander (2016), Foo et al. (2017), and Gruber et al. (1999) document the effect of changes in hospital and physician reimbursement prices on the use of C-sections. Gruber and Owings (1996) find that C-section use responds to expected future shocks to physician income. Spetz et al. (2001) find that C-section use responds to physician financial and leisure incentives for patients in group model Health Maintenance Organizations (HMOs). Yang et al. (2009) find that malpractice lawsuit reform affects the use of vaginal births (versus C-sections) in births following previous C-sections.

[11] Among Organisation for Economic Co-operation and Development (OECD) countries, the United States ranked 26$^{\text{th}}$ in infant mortality as of 2010 (CDC, 2014). Rosenberg (2016) quotes Jeffrey Ecker, the chairman of the American Congress of Obstetricians and Gynecologists' committee on obstetric practice: "[The rise of C-section rates] has not been paralleled by any important fall in rates of things like cerebral palsy."

[12] C-sections, relative to vaginal births, are associated with higher risks of morbidity, infection,

with an increased likelihood of subsequent C-sections and complications in future pregnancies (Kozhimannil et al., 2013). In summary, C-sections are a treatment insurers are have an incentive to influence, a treatment likely to respond to insurer influence, and a treatment whose reduction has implications for health care costs and patient welfare.

1.2 Theoretical Framework: How Insurer Competition Can Increase C-Sections

I develop a stylized model to formalize the intuition about how insurer competition can increase C-sections. Competition can create a mechanism through which spillover of insurer cost reduction can increase the use of C-sections. Patients live in a single market where n insurers contract with a single hospital.[13] Patients are treated for a single medical condition: childbirth. They buy insurance and subsequently receive treatment. There are two treatment options: patients may either deliver by vaginal birth (low cost to the insurer) or by C-section (high cost). The hospital chooses the treatment to minimize its cost, resulting in over-prescription of C-sections from the insurers' perspective. Insurers can invest to reduce the hospital's cost of performing vaginal births for their patients in order to decrease the number of C-sections performed.

To model investment spillover, I allow an insurer's investment to also reduce the hospital's cost of performing vaginal births for patients of rival insurers. This investment spillover creates a potential deterrent against insurers investing to limit the number of C-sections performed by the hospital. Through differentiated product Bertrand competition, if an insurer invests, she is also forced to reduce her premium and therefore profits because of the reduction to her rivals' costs. Competition causes insurers to limit their investment to reduce C-sections due to spillover. As a result, insurer competition can increase the number of C-sections performed.

blood clots, and emergency hysterectomy in mothers as well as asphyxia, respiratory and pulmonary disorders in infants (Johnson and Rehavi, 2016; Kozhimannil et al., 2013).

[13] For the purposes of this model, there is one provider which I refer to as the hospital. In particular, I am treating the physician and the hospital as the same entity to simplify the model.

1.2.1 Hospital Treatment Decision Framework

For each patient, the hospital chooses which treatment to perform in order to minimize its costs given patient symptoms. The hospital faces two treatment options: delivering the child by vaginal birth, denoted VB, or by C-section, CS. There is a continuum of patients uniformly distributed on a Hotelling line in their medical symptoms, S, ranked on appropriateness for VB to CS. This approach is similar to Chandra and Staiger (2006), Currie and MacLeod (2016), and Johnson and Rehavi (2016). I normalize S to lie in the interval [0,1] where 0 represents the treatment choice of VB and 1 represents the choice of CS.[14] The hospital incurs a cost $t(S)$ for choosing a treatment. I model $t(S)$ as a linear function of the geometric distance between a patient's symptoms S and their treatment choice (0 or 1). Intuitively, one can consider this the cost to the hospital of jointly deciding the treatment with the patient; the less a patient's symptoms translate to a particular treatment (the greater the geometric distance from S to either 0 or 1), the more costly the treatment is for the hospital to perform. This is similar to the "induced" treatment literature (namely Gruber and Owings, 1996) which models providers as incurring a cost (be it ethical, financial, or professional) for performing treatments that may not directly correlate with patient symptoms.

In addition to the cost of jointly determining treatment with the patient $t(S)$, the hospital faces an input cost of performing each treatment, d_τ. I assume the hospital faces a higher input cost for vaginal births than C-sections, $d_{VB} > d_{CS}$.[15] I normalize d_{CS} to zero and let $d = d_{VB}$. Because the hospital receives higher a reimbursement from performing C-sections than vaginal births, the input cost d internalizes the financial opportunity cost of performing vaginal births.[16] Given a patient with symptoms S, the hospital chooses $\tau \in \{CS, VB\}$ to minimize their cost of treatment $D(\tau; S, d, t)$:

$$\min_{\tau \in \{CS,VB\}} D(\tau; S, d, t) = \begin{cases} d + t * S & \text{if } \tau = VB \\ t * (1 - S) & \text{if } \tau = CS \end{cases} \tag{1.2.1}$$

[14] For example, a patient who previously had a C-section, which medically makes a subsequent C-section much more necessary, would have a symptom value S close to 1. We can also interpret S as incorporating patient preferences either for or against C-sections.

[15] For a more compete discussion, see Section 1.1.4.

[16] This implicitly assumes $d > r_{CS} - r_{VB}$ where r_{CS}, r_{VB} are the reimbursements for C-section and vaginal birth, respectively.

As seen in Figure 1, the solution to the hospital's cost minimization problem defines a threshold symptom level for the hospital's treatment decision: $\hat{S}(d) = \frac{t - d}{2t}$. The hospital performs vaginal deliveries for patients with symptoms $S < \hat{S}(d)$, and C-sections for patients with $S > \hat{S}(d)$. Due to the uniform distribution of patient symptoms, this threshold can also be interpreted as the percentage of patients receiving vaginal births. If there was no difference in the hospital's input cost between vaginal births and C-sections (if $d = 0$) the decision threshold would be $\hat{S} = \frac{1}{2}$. From an insurer's perspective, patients with symptoms $S \in [\frac{t - d}{2t}, \frac{1}{2}]$ receive C-sections when they are more medically suited for vaginal deliveries.

1.2.2 Insurer Investment

The threshold symptom level $\hat{S}(d)$, and thus the number of C-sections, is decreasing in the hospital's relative input cost of vaginal births d. If an insurer lowers the hospital's input cost of performing vaginal births, she can reduce the number of C-sections performed. Insurers can invest x to reduce the hospital's relative input cost d, as illustrated in Figure 2. For example, an insurer could invest by providing a bonus to the hospital if it reduces their total annual reimbursements to a certain level.[17] Assuming for the moment that only insurer i invests, the hospital's input cost for performing vaginal births for patients of insurer i is now their original input cost minus insurer i's investment (x_i): $d - x_i$. Following d'Aspremont and Jaquemin (1988) and Qiu (1997), in order to invest x_i, the insurer must pay $V(x_i) = \frac{\nu x_i^2}{2}$. Investment costs are fixed for simplicity and quadratic to capture diminishing returns to investment. I assume that the efficiency of investment (ν) is the same for all insurers.

[17] Gaynor et al. (2004) note that HMOs frequently use this type of incentive scheme to influence hospitals and physicians to provide treatments that internalize insurer cost concerns.

In this example, while the insurer makes a fixed payment (bonus) to hospital, the insurer's goal is to reduce expensive treatments by offseting the hospital's lost revenue from performing treatments with low reimbursement costs. The effect of this bonus is to reduce the hospital's input cost for performing vaginal births (the treatment with the lower reimbursement cost) for the marginal patient by lowering the hospital's financial opportunity cost. In my context, we can interpret this reduction to the hospital's input cost for the marginal patient as the amount of investment, x, even though the insurer actually pays a fixed ammount for that investment $V(x)$ (the bonus).

Investment Spillover

The insurer's goal of investing in cost-reduction is to influence a hospital's treatment style. In doing so, however, the insurer can create externalities that occur for patients of other insurers contracting with the hospital. For example, if insurer i invests to reduce the cost of vaginal deliveries for the hospital, the hospital may start to perform more vaginal births in circumstances where it previously performed C-sections. Consequently, the hospital may become more comfortable performing vaginal births in these situations for all of the patients it treats.[18] As a result, the investment reduces the hospital's input cost of vaginal births for patients of insurer i and also for patients of all other insurers.

Following Qiu (1997), I model investment spillover by allowing the hospital's input cost of vaginal births for other insurers' patients to be reduced by a fraction $\gamma \in [0, 1]$ of insurer i's investment (and vice-versa).[19] For a patient of insurer i, the hospital's input cost of vaginal births is $d - x_i - \sum_{j \neq i} \gamma x_j$. We can interpret γ as the degree to which a hospital practices similarly for patients of all insurers. For example, if a hospital were to practice completely differently for patients of different insurers $\gamma = 0$; on the other extreme, if the hospital practiced exactly the same for patients of all insurers $\gamma = 1$. I hold $\gamma > 0$ as fixed and exogenous to the model; I assume that investment spillover occurs.

Because of investment spillover, the percentage of patients of insurer i who receive C-sections can be expressed as decreasing function of all insurers' investment $\vec{x} = (x_1, ..., x_n)$:

[18] For example, as physicians at a hospital become more comfortable performing vaginal births in new clinical situations, they may have lower malpractice concerns for performing vaginal births in these contexts. In this way, the spillover from one insurer's investment can lower the hospital's input cost for performing vaginal births for all patients. This idea is similar to the idea of increased procedural skill through more frequently performing a treatment, as modeled in Currie and MacLeod (2016).

[19] Qiu (1997) develops a two firm model of differentiated product Bertrand competition with R&D investment that may reduce the rival's cost. I use the competition and investment spillover framework from Qiu (1997) in the context of insurer competition. In Qiu's model, the firm's cost function is simply $d - x_i - \gamma x_j$, where in this model the cost of the insurer is a function $f(d - x_i - \gamma x_j)$ of this cost to represent hospital treatment decisions. This can be seen by rewriting Equation (1.2.3). I additionally extend the competition-investment framework from Qiu (1997) using a similar demand function for n firms following Vives (1999).

$$1 - \hat{S}_i(\vec{x}) = \frac{t + d - x_i - \sum_{j \neq i} \gamma x_j}{2t} \tag{1.2.2}$$

Investment Spillover and Insurer Costs

Insurer i's cost is determined by the reimbursements she must pay to the hospital for each treatment τ, r_τ, and the cost she pays for any investment.[20] The reimbursement price for C-sections is greater than the reimbursement price for vaginal births: $r_{CS} > r_{VB}$.[21] Insurer i's expected cost per-patient is the product of the reimbursement for each treatment and the probability a patient receives that treatment:[22]

$$c_i(\vec{x}) = r_{VB} * \hat{S}(\vec{x}) + r_{CS} * [1 - \hat{S}(\vec{x})] \tag{1.2.3}$$

When insurer i invests she also reduce the number of C-sections insurer j must reimburse because of investment spillover. Consider the case of two insurers contracting with the hospital. Insurer i's investment reduces insurer j's cost, illustrated in Figure 3. As insurer i invests, she simultaneously reduce the hospital's cost of performing vaginal births for their own patients and also for patients of insurer j. As a result, insurer i's investment lowers the likelihood that patients of both insurers receive C-sections, lowering each insurer's expected cost per-patient.

[20] More formally, for simplicity I am assuming that insurers do not have any costs on top of their reimbursement and investment costs (i.e., any administrative costs).

[21] This inequality reflects the well documented difference between the reimbursement prices for C-sections and vaginal birth (Johnson and Rehavi, 2016).

[22] Due to the uniform distribution of patient symptoms the probability of receiving VB is equal to the proportion of patients receiving VB (likewise for CS): $\text{pr}(\tau = VB) = \hat{S}$, $\text{pr}(\tau = CS) = 1 - \hat{S}$.

1.2.3 Insurer Profit Maximization

Insurer i derives revenue from charging each of their consumers a premium, p_i. Similar to Qiu (1997) and Vives (1999), I use the following linear demand function for insurer i as a function of the premiums from all n insurers:[23]

$$q_i(p_1, ..., p_n) \;=\; a_n(\delta) - b_n(\delta)p_i + z_n(\delta)\sum_{j\neq i} p_j \tag{1.2.4}$$

Insurers engage in differentiated product Bertrand competition. If one insurer reduces their premium, she can simultaneously increase their own demand and also reduce the demand of all the other insurers. The degree to which a single insurer is able to affect the demand of other insurers through lowering their premium is determined by $\frac{\partial q_i}{\partial p_j} = z_n(\delta)$. $\delta \in (0,1)$ is the degree of product differentiation between any pair of insurers i and j.[24] As δ increases towards one, that is as products become closer substitutes, $z_n(\delta)$ increases; insurer i's demand is more sensitive to each rival insurer j's premium.[25] In this sense, we can consider δ as a measure of competition between insurers. If δ is higher, there is more competition in the market because each insurer's demand is more responsive to the change in another insurer's premium.

Each insurer chooses their level of investment and then premium to maximize their profits. I solve for the Nash equilibrium investment choices through backward induction, first solving for each insurer's premium choice given each insurers' investment choices:

$$p_i^*(\vec{x}) \;=\; \arg\max_{p_i}\; [a_n(\delta) - b_n(\delta)p_i + z_n(\delta)\sum_{j\neq i} p_j] * [p_i - c_i(\vec{x})] - V(x_i) \tag{1.2.5}$$

I use the premium decision rules to solve for the insurer i's optimal investment decision:[26]

$$x_i^* \;=\; \arg\max_{x_i}\; q_i(p_1^*(\vec{x}), ..., p_n^*(\vec{x})) * [p_i^*(\vec{x}) - c_i(\vec{x})] - V(x_i) \tag{1.2.6}$$

[23]For a derivation of the demand function, see Section A.1.2 in the Mathematical Appendix. Note that $a_n(\delta)$, $b_n(\delta)$, $z_n(\delta)$ depend on the number of insurers n. In what follows, I address any cases where this fact affects the analysis.

[24]This definition implicitly assumes products are symmetrically differentiated for simplicity.

[25]Note that a_n, b_n also depend on δ. I address any cases where this fact affects the analysis.

[26]For a further discussion of the solutions to these maximization problems see Sections A.1.3, A.1.4 in the Mathematical Appendix.

1.2.4 How Competition Affects Insurer Investment, C-sections

An insurer's primary benefit to investing is that by decreasing the hospital's relative cost of performing vaginal births, she can decrease the probability that her patients receive C-sections (the more expensive treatment option). Investment allows insurers to lower their expected cost per-patient relative to their revenue per-patient (premium); insurers increase their markup by investing. The investing insurer, in turn, can lower their premium slightly relative to their rivals to capture demand. Using the first order condition from insurer i's investing decision, we can see the effect of insurer i's investment on their profits:

$$\frac{\partial \pi_i}{\partial x_i} = q_i * \underbrace{\left[\frac{\partial p_i^*}{\partial x_i} - \frac{\partial c_i}{\partial x_i}\right]}_{\text{Effect on Markup}} + \underbrace{\left[\frac{\partial q_i}{\partial p_i}\frac{\partial p_i^*}{\partial x_i} + \sum_{j\neq i}\frac{\partial q_i}{\partial p_j}\frac{\partial p_j^*}{\partial x_i}\right]}_{\text{Effect on Demand}}(p_i^*(\vec{x}) - c_i(\vec{x})) - \underbrace{\frac{dV}{dx_i}}_{\text{Cost of Investment}} \tag{1.2.7}$$

Spillover of insurer investment affects insurer i's investment decision by distorting their return on investment in cost reduction. First, consider the effect of insurer i's investment on their markup. Using the first order condition from insurer i's premium choice, we can see the effect that each insurer's investment and premium choices have on insurer i's premium:

$$p_i^* = \frac{a_n}{2b_n} + \frac{c_i(\vec{x})}{2} + \frac{z_n(\delta)}{2b_n(\delta)}\sum_{j\neq i} p_j \tag{1.2.8}$$

Using this condition, we can see how insurer i's investment affects their markup:

$$\frac{\partial(p_i^* - c_i)}{\partial x_i} = \underbrace{-\frac{1}{2}\left(\frac{\partial c_i}{\partial x_i}\right)}_{\text{direct effect on markup (+)}} + \underbrace{\frac{z_n(\delta)}{2b_n(\delta)}\sum_{j\neq i}\frac{\partial p_j}{\partial x_i}}_{\text{spillover effect on markup (-)}} \tag{1.2.9}$$

Insurer i's investment increases their markup by decreasing their marginal cost (their expected cost per-patient) by more than it decreases their premium ("direct effect on markup"); as seen in Equation (1.2.3): $\frac{\partial c_i}{\partial x_i} < 0$. However, because of investment spillover, insurer i's investment also decreases the marginal cost of all other insurers. Spillover allows the other insurers to similarly lower their own premiums in order to capture demand and increase profits. If there was no spillover ($\gamma = 0$), then insurer i's investment would not reduce the marginal cost for any other insurer j ($\frac{\partial c_j}{\partial x_i} = 0$). In the absence of spillover, another insurer j would therefore not be able to lower their premium due to lower marginal cost ($\frac{\partial p_j}{\partial x_i} = 0$). Thus, spillover creates a distortion by forcing insurer i to lower their own premium further than she would have in the absence of spillovers because other insurers lower their premiums ("spillover effect on markup"). As a result, spillover limits the positive effect of insurer i's investment on their markup.

Investment spillover similarly distorts the effect of insurer i's investment on their demand:

$$\frac{\partial q_i}{\partial x_i} = \underbrace{-b_n(\delta)\frac{\partial p_i^*}{\partial x_i}}_{\text{direct effect on demand (+)}} + \underbrace{z_n(\delta)\sum_{j\neq i}\frac{\partial p_j^*}{\partial x_i}}_{\text{spillover effect on demand (-)}} \tag{1.2.10}$$

Because insurer i's investment lowers their marginal cost, insurer i is able to increase their own demand by reducing their premium relative to their rivals' premiums ("direct effect on demand"). However, because spillover causes insurer i's investment to lower the costs for the other insurers, the other insurers at the hospital are also able to reduce their premiums ("spillover effect on demand"). This reduces the degree to which insurer i is able to increase their demand by lowering their premium relative to their rivals' premiums. Spillover therefore limits insurer i's ability to increase demand through investing. By limiting insurer i's ability to increase their markup and demand through investing, premium competition creates a mechanism through which spillover reduces insurers' return on investing in cost reduction.

1.2.5 Empirical Predictions

Using this theoretical framework it is possible to derive predictions in order to empirically test whether competition causes spillover to decrease C-sections. In particular, I can use the fact that the magnitude of the distortion to insurers' investment decision due to spillover is determined by the interaction of the number of insurers contracting with the hospital and the level of competition between the insurers. Mathematically, this is seen by rewriting the effect of insurer i's investment on their markup and demand, respectively:

$$\frac{\partial(p_i^* - c_i)}{\partial x_i} = \underbrace{-\frac{1}{2}\left(\frac{\partial c_i}{\partial x_i}\right)}_{\text{direct effect on markup (+)}} + \underbrace{z_n(\delta)(n-1)\left(\frac{1}{2b_n(\delta)}\frac{\partial p_j}{\partial x_i}\right)}_{\text{spillover effect on markup (-)}}$$

$$\frac{\partial q_i}{\partial x_i} = \underbrace{-b_n(\delta)\frac{\partial p_i^*}{\partial x_i}}_{\text{direct effect on demand (+)}} + \underbrace{z_n(\delta)(n-1)\frac{\partial p_j^*}{\partial x_i}}_{\text{spillover effect on demand (-)}}$$

Spillover's effect on both insurer i's markup and demand is increasing in the number of insurers contracting with the hospital.[27] As the number of insurers increases, the spillover from an individual insurer's investment decreases more insurers' costs. Investment spillover is therefore more problematic if the hospital contracts with more insurers because it allows more rival insurers to reduce their premiums. This places further downward pressure on insurer i's premium, reducing the degree to which she can lower her premium relative to her cost (reducing the increase in their markup from investing). It also reduces the degree to which insurer i is able to lower their premium relative to their rivals' (reducing the increase in their demand from investing). Therefore, as insurer i's investment affects more insurers at the hospital, their return on investment decreases.

Insurer i's optimal choice of investment decreases as the number of insurers increases. This is seen in Figure 4, which plots insurer i's optimal choice of investment as a function of the number of insurers contracting with the hospital. The model predicts that investment spillover creates a greater deterrent when the hospital contracts with a greater number of insurers. Intuitively, if physicians practice similarly

[27]Note that while the model is simplified to have only a single hospital in a single market, the number of insurers here captures the number of insurers at the hospital (not the number of insurers in the market). The number of insurers affects insurer i's investment decision because it represents the number of insurers whose costs are lowered by insurer i's investment *at the hospital*. Also, the number of insurers affects insurer i's investment decision because it represents the number of insurers that lower their premiums due to lower costs.

It is also important to note that $b_n(\delta)$ and $z_n(\delta)$ both depend on the number of insurers n. However, $\frac{\partial}{\partial n}\left|(n-1) * \frac{z_n(\delta)}{2b_n(\delta)}\right| > 0$. For a proof see Section A.1.3 in the Mathematical Appendix.

for patients of all insurers (if $\gamma > 0$), it follows that spillover should pose a larger problem to a particular insurer when the hospital treats more patients from other insurers.

Competition, however, is what causes insurer i to alter their investment decision due to spillover concerns. If insurer i's demand did not depend any other insurer's premiums (i.e., if there was no competition $z_n(\delta) = 0$), spillover would not limit insurer i's return on investing to either their markup or demand; spillover would not cause the same distortion in insurer i's investment decision. While the model is simplified to a single market, it is possible to compare markets with different levels of competition between insurers. If the level of competition between insurers in the market increases to $\delta' > \delta$, insurer i's demand will be more responsive to insurer j's premium: $z_n(\delta') > z_n(\delta)$. As a result, spillover would create a bigger distortion in insurer i's investment decision when the level of competition is higher.[28] If insurer i's demand were more sensitive to changes in another insurer j's premium, insurer i would be more sensitive to reducing insurer j's cost. Therefore, if the level of competition between the insurers increased, each insurer would be more reluctant to invest because their investment lowers their rivals' costs. This is also seen in Figure 4. As the level of competition between insurers exogenously increases to $\delta' > \delta$, the curve defining the relationship between the number of insurers at the hospital and insurer i's investment shifts down. While investment spillover creates a deterrent against insurer investment, the level of competition between the insurers determines the degree to which insurers respond to it.

Using insurers' optimal choices of investment, Figure 5 plots C-section likelihood as a function of the number of insurers at the hospital. Figure 5 illustrates the two main predictions of the theoretical framework. First, the proportion of C-sections performed increases with the number of insurers contracting with the hospital. An insurer's return on investment is lower at hospitals where there are more insurers due to spillover. Each insurer is less inclined to invest in limiting C-sections resulting in more C-sections performed. Second, if the level of competition increases, the number

[28] As seen in both the effect of insurer i's investment on their markup and demand, the size of the spillover effect is increasing in δ. Note that for this to be true in the case of the case of the effect insurer i's investment on demand, it must be the case that $z_n(\delta)$ is increasing at a faster rate in δ than $b_n(\delta)$. This is true for all values of $\delta \in (0, 1)$. For a proof see Section A.1.3 in the Mathematical Appendix.

of insurers has a larger effect on C-sections. As the level of competition increases, insurers are more sensitive to reducing their rivals' costs because their demand is more sensitive to changes in their rivals' premiums. Therefore, if the level of competition between insurers is higher, their investment is more sharply decreasing in the number of insurers at the hospital. Correspondingly, the number of C-sections performed is more sharply increasing in the number of insurers at the hospital. Competition inhibits insurers from limiting C-sections due to spillover concerns and results in a higher number of C-sections performed.

1.3 Using OSHPD Discharge Data to Estimate Insurer Competition's Effect on C-Sections

The theoretical framework demonstrates a mechanism for how insurer competition can increase the use of C-sections. Competition can increase the number of C-sections performed by inhibiting insurers from limiting C-sections due to spillover concerns. The main challenge to empirically testing if competition affects the use of C-sections through this mechanism is that I cannot directly observe the spillover of insurer cost reduction. However, the theoretical model predicts that spillover undermines insurers' return on liming C-sections more at hospitals that contract with more insurers. This prediction implies that to empirically test whether insurer competition increases the use of C-sections, I can ask two related, empirical questions: 1) Are C-sections likely at hospitals that contract with more insurers? 2) Is this effect larger at hospitals located in more competitive insurance markets?

For my empirical analysis, I focus on the effect of Health Maintenance Organization (HMO) competition on C-section use.[29] I use hospital discharge data from the California Office of Statewide Health Planning and Development (OSHPD) to approximate the two key parameters from my theoretical model: the number of HMOs at

[29] As discussed in Section 1.1.1, while there are other types of private insurance plans, HMOs are most likely to engage in cost-reduction investment and therefore the most relevant for my analysis. Other studies related to the spillover of insurer investment (namely, Chernew et al., 2004; Maeng et al., 2010) also limit their analysis to HMOs. HMOs and other types of private insurance (i.e., Fee-For-Service, or Preferred Provider Organizations) are not perfect substitutes; HMOs are typically less expensive and have more restrictions (Chernew et al., 2004). In particular, I assume HMOs principally compete with each other.

each hospital and the level of HMO competition in each market. I measure the degree to which hospitals contract with multiple HMOs using the concentration of HMOs at each hospital. The specific measure of concentration I use is the Herfindahl-Hirschman Index (HHI). I use the HHI of HMO plans at the market level to approximate HMO competition.

1.3.1 Data Sources: OSHPD Discharge Data

I principally use the OSHPD discharge data from 2005 to 2013. The discharge data include all discharges from California hospitals over my sample time period. The data allow me to observe patients' treatments, demographic characteristics, diagnostic information, insurance information, and treatment hospital. I supplement the discharge data with data from the American Community Survey (ACS) for 2005-2013 and the American Hospital Association (AHA) Annual Survey from 2005-2012.

The OSHPD discharge data contains data on patient insurance plans for patients with HMO insurance.[30] This data feature allows me to create measures of HMO concentration at both the hospital and market level. Because I am ultimately interested in estimating the impact of HMO competition on C-section prevalence, I restrict my analysis to commercial HMOs and Medi-Cal (Medicaid) HMOs that compete against commercial HMOs.[31]

1.3.2 Measuring the Number of HMOs at Each Hospital

My goal is to use the number of HMOs contracting with each hospital as an observable measure of variation in HMO spillover concerns at each hospital. As discussed in Section 1.1.2 providers tend to practice similarly for patients of all insurers. Because of this feature, any persistent change in a provider's practice style induced by a single

[30]For a more complete discussion of how I use the OSHPD discharge data to identify the insurance plans of patients with HMO insurance see Section A.2.1 in the Data Appendix.

[31]Medi-Cal is California's Medicaid agency. Patients in some counties are able to enroll in Medi-Cal HMO plans. However, Medi-Cal HMOs are structured differently by county. In some counties, Medi-Cal HMOs are offered by commercial insurers or compete against such HMOs. I include these Medi-Cal HMOs in my analysis, but exclude Medi-Cal HMOs that are not offered by *and* do not compete against commercial insurers. For a more complete discussion, see the Section A.2.2 in the Data Appendix.

HMO is likely to affect patients of all insurers contracting with that provider. Conditional on the assumption that this spillover occurs, the theoretical model predicts that spillover will present a greater deterrent to cost reduction for a given HMO at hospitals that treat more patients from rival HMOs. For this reason, Maeng et al. (2010) similarly use the overlap in HMO physician networks as a way of measuring which physician groups were more likely to have HMO investment spillover.[32]

I use HMO concentration to measure the degree to which hospitals contract with multiple HMOs. If a hospital is highly concentrated, a smaller number of HMOs control more patients at that hospital. From the perspective of each HMO contracting with the hospital, a highly concentrated hospital treats fewer patients of rival HMOs. Therefore, HMOs should be more concerned about spillover at hospitals where HMOs are less concentrated. The specific measure of hospital level HMO concentration I use is the HHI of HMO birth discharges at each hospital. HHI is computed as the sum of squared HMO shares of birth discharges at each hospital.[33] HHI is preferable to the number of HMOs contracting with the hospital because it additionally captures how discharges are distributed among insurers within the hospital.[34] For notational simplicity, from this point forward I refer to the HHI of HMO birth discharges at the hospital level as "hospital level HHI."

Using hospital level HHI to measure variation in HMO spillover concerns at each hospital in my empirical analysis implicitly relies on the assumption that provider practice styles are persistent across patients' insurers. In other words, I assume that spillover occurs. The theoretical prediction that spillover should pose a greater threat to HMOs at hospitals that contract with a greater number of HMOs relies

[32] Maeng et al. (2010) estimate the effect of overlap in HMOs' physician networks on HMO quality scores. They argue that the effect on quality scores is caused by HMOs under-investing in quality improvements at physician practices due to fear of simultaneously increasing the quality for other HMOs contracting with those practices (investment spillover). In this way, they are attempting to approximate what I call "spillover" at different physician practices. They use two measures of physician overlap: the percentage of physicians who are in the same network for each pair of HMOs they observe; the average number of HMO contracts held by physicians in each HMO's network within each market.

[33] For a complete explanation of how I construct the HHI of HMO birth discharges at each hospital see Section A.2.3 in the Data Appendix.

[34] For example, consider a hospital with two HMO where one controls 99% of discharges. Concentration in that hospital is very different than a hospital where each HMO controls 50%. HHI captures on this difference where the number of HMOs contracting with the hospital does not.

on this assumption. While this assumption is generally consistent with the evidence presented by previous literature, the failure of this assumption would undermine my interpretation for the effect of hospital level HHI on C-section prevalence. After my primary analysis, I provide evidence to support this assumption in Section 1.5.

1.3.3 Measuring HMO Competition

While I measure variation in HMO spillover concerns at the hospital level, I measure HMO competition at the market level. I define a market to be a Health Insurance Rating Area (HRA). Due to the Patient Protection and Affordable Care Act of 2010 (ACA), insurance plans participating in the newly created individual private insurance exchanges are not allowed to vary their premiums within a rating area. I consider these areas as a reasonable approximation of geographic HMO markets.[35]

I approximate the degree of competition within the HMO market containing each hospital using market level HMO concentration. In my theoretical framework, competition determines the degree to which an insurer's demand is affected by a rival insurer's premium. In concentrated markets, HMOs face less pressure to compete on premiums because fewer firms control the majority of the market. Larger HMOs in more concentrated markets can exploit market power when setting premiums. Therefore, their demand is less affected by the premiums set by other HMOs. More concentrated markets are less competitive. I compute the HHI as the sum of squared HMO shares of all hospital discharges within a HRA to measure HMO concentration at the market (HRA) level.[36] For notational simplicity, I refer to the HHI of all HMO discharges at the market level as "market level HHI." To my knowledge, I am the first to use the patient insurance information contained in the OSHPD discharge data to create a measure of HMO market structure. This is similar in spirit to Ho and Pakes

[35]My sample predates the implementation of the ACA marketplaces. The Centers for Medicare and Medicaid Services (CMS) states that rating areas must be chosen (by states) to "lead to stability in rates over time, [and] apply uniformly to all health insurance issuers *in a market*" (CMS, 2015). Given that the ACA aims to regulate premium competition within these regions, it follows that these rating areas constitute geographic regions in which insurers were previously competing with each other over premiums. As California could have chosen counties for this purpose, as many other states did, and elected to form these new rating areas it is arguable that rating areas are a preferable definition of a geographic insurance market.

[36]As premium pricing decisions may be influenced by competition for all types of patients (not just birth patients), I calculate the HHI for all discharges at the market level.

(2014) who use OSHPD discharge data to identify contracting relationships between HMOs and hospitals using the same patient insurance data.

One potential concern with my approach is that a discharge based measure of market level HMO concentration is based on patients who receive treatment rather than taking into account all patients who enroll with HMOs. If patients from certain HMOs are disproportionately likely to receive treatment, my market level concentration measure may suffer from measurement error. To address this concern, I aggregate discharges to the state level and compute annual, state-wide HMO shares. By comparison I calculate annual, state-wide HMO shares (using the same plans) from state-wide enrollment data from HMO annual financial reports to the California Department of Managed Health Care. The discharged-based measures are very closely related with enrollment-measures, alleviating the concern that discharge-based measures may misrepresent concentration. The correlation coefficient for the annual enrollment shares and discharge shares is 0.977.

1.3.4 Sample Description

I use observations where the patient is the mother and identify treatment and diagnoses using the Diagnosis Related Group (MS-DRG) codes and ICD-9 diagnostic and procedure codes. I restrict my primary sample to women who are classified by the American College of Obstetrician-Gynecologists as lower risk for C-sections, following the methodology of Kozhimannil et al. (2013).[37] By doing so, I am excluding pregnancies with ex-ante conditions identified by the medical literature as typically necessitating a C-section and therefore limiting my analysis to cases where physicians have more clinical flexibility.

Perhaps the most notable sample restriction is omitting Kaiser Permanente hospitals and patients from my sample. Kaiser is a vertically integrated HMO with a single parent company owning both the insurance plan and care providers. Through Kaiser insurance, patients only have access to Kaiser providers, and only patients with Kaiser insurance may access Kaiser hospitals (Ho, 2009). Because Kaiser hospitals only contract with Kaiser insurance, there is no risk of spillover at these hospitals.

[37] For a definition of low risk births and a more complete justification for my sample restrictions see Section A.2.4 in the Data Appendix.

Therefore, at these hospitals, HMO competition in the market containing the hospitals should not affect Kaiser insurance's incentive to limit C-sections due to spillover concerns. Hence, at these hospitals, I cannot test for the proposed mechanism of how HMO competition can increase C-sections. For a full complete discussion of my sample restrictions see Section A.2.4 in the Data Appendix.

Table 1.1 displays summary statistics for the full sample of HMO births, low-risk HMO births, and my baseline sample. C-section rates are substantially lower in my baseline sample compared to the full sample (13.2% compared to 31.6%). This disparity is almost entirely due to restricting to low-risk births. The most notable disparity between the full sample of relevant births and my baseline sample is between the HMO concentration measures at both the hospital and market level. The average HMO's share of hospital births in my baseline sample is almost half that in the full sample of births available (31.5% compared to 52.7%). This difference is mostly due to excluding Kaiser hospitals; the average plan share at all Kaiser hospitals is very close to one. There is a corresponding difference in hospital level HHI between the full and baseline samples. In the baseline sample, the average hospital would be classified as highly concentrated (HHI of 0.311) and the average market would be classified as moderately concentrated (0.208) under the Department of Justice and Federal Trade Commissions Horizontal Merger Guidelines.[38]

[38]Typically HHI is measured on a 0 to 10,000 scale. I scale HHI to lie in the interval [0,1].

1.4 Main Results: Estimating How the Effect of Hospital Level HHI on C-section Use Varies with Market Level HHI

Using my empirical measures of the number of HMOs at each hospital and HMO competition, I can rephrase my two empirical questions: 1) Are C-sections more likely at hospitals with lower HMO concentration? 2) Is this effect larger at hospitals located in more competitive (less concentrated) HMO markets?

1.4.1 Least Squares Analysis

Estimating Equation

I estimate a linear probability model using Ordinary Least Squares (OLS) for the likelihood that patient j of HMO i receives a C-section at hospital h in year t:

$$\begin{aligned}\text{C-section}_{jiht} &= \beta_0 + \beta_1 \text{HHI, Hos.}_{ht} + \beta_2 \text{HHI, Mkt.}_{ht} \\ &\quad + \beta_3 \text{HHI, Hos.}_{ht} * \text{HHI, Mkt.}_{ht} + \beta_4 X_{jt} + \beta_5 H_{ht} + \alpha_h + \alpha_i + \alpha_t + \varepsilon_{jiht}\end{aligned} \tag{1.4.1}$$

C-section$_{jiht}$ is an indicator for whether the patient received a C-section. HHI, Hos.$_{ht}$ is the HHI of HMO birth discharges at hospital h in year t; HHI, Mkt.$_{ht}$ is the HHI of HMO discharges in the market (HRA) containing hospital h in year t. X_{jt} is a vector of patient characteristics containing a patient's age, race, ethnicity; complications arising during labor predictive of receiving a C-section;[39] and an indicator for whether

[39] A patient's race is classified as one of the following: Asian, Black, Native American/Eskimo/Aleut, Other (with White being the excluded category). A patient's ethnicity is an indicator for whether she is Hispanic. I control for the following labor complications: cord prolapse, dystocia, fetal distress, herpes, maternal distress, and previa. These measures are mentioned as a significant C-section predictors by several of the papers in both medical and health economics literature (Currie and MacLeod, 2016; Foo et al., 2017; Gruber et al., 1999; Gruber and Owings, 1996; Kozhimannil et al., 2013; Srinivas et al., 2010; Spetz et al., 2001).

patients are part of a Medi-Cal HMO, and the type of Medi-Cal HMO.[40] H_{ht} includes hospital characteristics: the number of hospitals in each hospital's county, the natural logarithm of the number of birth discharges at each hospital. I include hospital, HMO, and year fixed effects.

The effects of hospital and market level HHI on C-section use are identified by variation in HMO concentration within hospitals and markets over time. Figures 6 and 7 provide a visual depiction of this variation by plotting the distribution of annual percentage changes in both hospital and market level HHI in my sample, respectively.

My first empirical question concerns the marginal effect of hospital level HMO concentration on the probability of receiving a C-section. The coefficients of interest are both β_1 and β_3. I expect that C-sections are more likely at hospitals where HMOs are less concentrated - at hospitals where discharges are spread among more HMOs (where spillover should pose a greater deterrent to insurer cost reduction). Therefore, the marginal effect of hospital level HHI on C-sections should be negative:

$$\frac{\partial \text{ C-section}_{jiht}}{\partial \text{ HHI, Hos.}_{ht}} = \beta_1 + \beta_3 * \text{HHI, Mkt.}_{ht} < 0$$

My second empirical question asks how the effect of hospital level HHI on C-section use varies with market level HHI. Here, β_3 is the coefficient of interest. If the effect of hospital level HHI on C-sections is larger at hospitals in competitive HMO markets, it will be smaller in more concentrated HMO markets (as competition and concentration are negatively correlated). Therefore, the size of hospital level HHI's effect on C-section likelihood should vary negatively with market level HHI :[41]

$$\frac{\partial \left| \frac{\partial \text{ C-section}_{jiht}}{\partial \text{ HHI, Hos.}_{ht}} \right|}{\partial \text{ HHI, Mkt.}_{ht}} \;=\; -\beta_3 \;<\; 0 \;\;;\;\; \beta_3 > 0$$

Taken together, these two inequalities show that I can answer my two empirical questions by estimating Equation (1.4.1) and testing if $\beta_1 < 0$ and if $\beta_3 > 0$.

[40]I include two indicator variables for which type of Medi-Cal HMO patients are a part of. First I include an indicator for whether Medi-Cal HMO patients are part of a "Local Initiative" plan in a Two Plan county. The second is an indicator for whether Medi-Cal HMO patients are part of a Medi-Cal only HMO plan in a Geographic Managed Care county. For a more complete discussion, see Section A.2.2 in the Data Appendix.

[41]This assumes that the previous inequality holds.

Results

Table 1.2, Column 1 (Panel A) presents the OLS estimates of Equation (1.4.1) for the baseline sample. The estimates for both of the coefficients of interest are statistically significant in the expected directions. There is a negative association between Hospital level HHI and C-section use that is statistically significant at the one percent level. The interaction of hospital and market level HMO HHI is positively associated with C-section use and this association is also significant at the one-percent level.

The estimates from Equation (1.4.1) support two primary findings. First, C-sections are more likely at hospitals with lower HMO concentration. Using the estimates for the coefficients of interest, I compute the marginal effect of hospital level HHI on C-section likelihood in Panel B of Table 1.2. At an average hospital in an average market, a 10% decrease in hospital level HHI would be associated with a 0.5% increase (0.07 percentage points - pp) in C-section use for HMO patients giving birth at that hospital.[42]

The second finding is that the negative effect of hospital level HHI on C-section use is larger in magnitude at hospitals located in more competitive (less concentrated) HMO markets. In Table 1.3 (Panel B), I report the effect of a 10% decrease in hospital level HHI on C-section likelihood at an average hospital but vary the market level HHI. At an average hospital, the effect of a 10% decrease in hospital level HHI would be associated with a 0.7% increase (0.10 pp) in C-section use if the hospital was located in a more competitive market (25^{th} percentile of market level HHI). By comparison, the same 10% decrease in hospital level HHI would be associated with a 0.4% increase (0.05 pp) in C-section use if the hospital was located in a less competitive market (75^{th} percentile of market level HHI). These results imply that hospital level HHI should have a larger effect on C-section use at hospitals located in more competitive HMO markets.

Table 1.2 presents the estimates of Equation (1.4.1) when I relax the sample restrictions to include patients who are high risk of receiving a C-section (Column

[42] A 10% decrease in hospital level HHI at an average hospital would be a 311 point (0.03) decrease. By comparison, a one standard deviation decrease in hospital level HHI would be a 1846 point (0.19) decrease.

2).[43] The estimates for both of the coefficients of interest are consistent in sign, and are statistically significant at the one-percent level. The estimates for both of the coefficients of interest are smaller in magnitude for the sample including high risk births. The marginal effect of a decrease in hospital level HHI for patients of all risk levels is noticeably smaller than when restricting to low-risk births (0.1% compared to 0.5%). This result is consistent with the hypothesis that providers have less clinical flexibility for patients who are classified as high risk of receiving a C-section.

Of the other control variables included, there are a few significant effects worth noting. Medi-Cal patients were less likely to receive a C-section compared to non Medi-Cal HMO patients. Alexander (2016) discusses how women insured by Medicaid are less likely to receive C-sections than comparable women with private insurance. Age and all of the labor complication variables showed statistically significant coefficients at the one-percent level in the expected directions: older patients and patients who developed labor complications were more likely to receive C-sections. One concern with using OLS to estimate an equation with a binary dependent variable is that the estimates may predict values of the dependent variable that lie outside of the interval [0,1]. However, the estimates of Equation (1.4.1) predict values of C-section likelihood that lie within [0,1] for 93.3% of the observations. Another potential concern is that hospital treatment decisions could be correlated within hospitals over time, however the results are also robust to clustering standard errors at the hospital level (Table 1.4).[44] It could also be the case that HRAs may not present an accurate representation of geographic HMO markets because some of the HRAs are non-contiguous. However, the results are robust to using alternative geographic market definitions.[45]

[43] When using the sample of all births, I additionally include indicators for each of the conditions that would preclude a patient from being classified as low risk for a C-section. These conditions are listed in Section A.2.4 in the Data Appendix.

[44] When I cluster standard errors at the hospital level, both of the coefficients of interest are still statistically significant at the 10% level.

[45] When I omit non-contiguous HRAs, and alternatively define HMO markets as Hospital Referral Regions (HRR) using the Dartmouth Atlas and define HMO markets as counties the estimates of the baseline specification yield qualitatively and quantitatively similar conclusions. These results are presented in Table 1.4.

Engogeneity Concerns

By using OLS to estimate Equation (1.4.1), I assume that the variation in both hospital and market level HHI is exogenous. Any unobserved factors related to a patient's likelihood of receiving a C-section are assumed to be unrelated to my explanatory variables: hospital and market level HHI. This assumption is problematic because hospital and market level HHI are not random. In particular, HMO concentration at the hospital and market level are the result of HMOs' choices to contract with particular hospitals and to maintain a presence in particular markets. It may be the case that HMOs decide to contract with hospitals or participate in markets because of unobservable hospital or market characteristics correlated with C-section use. For example, the staff at a particular hospital could prefer to avoid C-sections whenever possible. Because HMOs would be more inclined to contract with this hospital, these unobserved preferences would be correlated with both a low C-section rate and low HMO concentration.[46] In this example, the OLS estimate for the effect of hospital level HHI on C-section likelihood would incorporate the effect of the unobserved preferences resulting in a biased estimate; the OLS estimate of hospital level HHI's effect on C-section likelihood I observe would be lower than the true effect. It is similarly possible that unobserved physician and HMO characteristics could be correlated with a patient's likelihood of receiving a C-section likelihood and hospital level HMO concentration.[47]

If the exogeneity assumption is not valid, the OLS estimates may be biased. By including hospital and HMO fixed effects, I am able to account for unobserved heterogeneity resulting from time-invariant, hospital, HMO and market characteristics

[46]Insurers should be more willing to contract with hospitals where they can pay lower reimbursement costs. If a hospital performs fewer C-sections, an insurer would have lower total reimbursement costs because C-sections are typically more expensive to reimburse than vaginal births. For this reason, a hospital's C-section rate is a factor insurers (i.e., HMOs) consider when deciding whether to contract with hospitals (Rosenberg, 2016).

[47]Hospital and market level HMO concentration are also determined by a patient's choice of hospital. A patient's delivery hospital may be affected by the patient's choice of HMO and also physician. It is possible that a patient may choose a HMO or physician based off of unobserved characteristics correlated with C-section use who may steer the patient to a particular hospital. For example, a physician could steer patients preferring C-sections to a higher quality hospital where many HMOs contract. In this case, unobserved physician characteristics (determining a patient's choice of physician) could be correlated with a high C-section likelihood and low HMO concentration.

correlated with hospital and market level HHI.[48] Therefore, unobserved hospital preferences for limiting C-sections that were constant over time, for example, would not bias my OLS estimates. Because I do not observe any physician information in my data, I cannot include physician fixed effects. My OLS estimates assume that any unobserved physician characteristics related to C-section use are unrelated to hospital and market level HMO concentration. More generally, fixed effects are not able to account for changes in unobserved factors correlated with my explanatory variables over time. The fixed effects also cannot address reverse causality if changes in C-section rates cause changes in hospital and market level HMO concentration, rather than the other way around. For example, it could be the case that insurers choose to contract with hospitals with low C-section rates.

1.4.2 Instrumental Variables Analysis

To address the potential endogeneity of hospital and market level HHI in Equation (1.4.1), I use a set of four instrumental variables based on the prior literature. They are: the natural logarithm of population for each hospital's county; the percentage of the population aged 25-29 and greater than 65 for each hospital's market (HRA); and the interaction of the natural logarithm of population for each hospital's county and the percentage of the population greater than 65 for each hospital's market (HRA). For the instrumental variables to be valid they must be correlated with hospital and market level HHI and must be uncorrelated with the likelihood of a patient receiving a C-section. Conditional on these criteria, using instrumental variables will result in consistent, causal estimates for the effect of hospital and market level HHI on C-section likelihood.

Identification

Conceptually, my instrumental variables are based on geographic characteristics correlated with HMO concentration at the hospital and market level but plausibly exogenous to a patient's likelihood of receiving a C-section. This strategy follows the approach of several studies reviewed by Baker (2003) that attempt to instrument

[48]Because hospitals do not change markets over time, hospital fixed effects incorporate unobserved, time-invariant market characteristics.

for market level HMO penetration. The population of the county containing a hospital should be positively correlated with HMO concentration at the hospital level. Chernew et al. (2004) study factors related to overlap in HMOs' physician networks. They find that one of the strongest relationships is the negative correlation between the population of a hospital's metropolitan statistical area and overlap. If HMOs are more concentrated at a hospital, there would be less overlap between HMOs at that hospital because there are more patients from a fewer number of plans compared to a less concentrated hospital. There should be a positive relationship between county population and hospital level HHI. I use the natural logarithm of the population of the county containing each hospital as an instrument for hospital level HHI.

The percentage of a market's population aged 25-29 and percentage of a market's population older than 65 should be correlated with HMOs' decisions to participate in markets (and thus, market level HHI). This approach is similar to Tebaldi (2017) who uses market age composition variables to instrument for insurer premiums. I expect that markets with large younger populations will be more attractive to HMOs because younger adults are more likely to be healthy and therefore less expensive to insure. Adults over the age of 65 are eligible for Medicare. If a greater proportion of a market's population is enrolled in Medicare, the size of the private insurance market place would be correspondingly smaller, and thus less attractive private insurers. I expect there to be more HMO competition (less concentration) when younger populations are larger and older populations are smaller. As an instrumental variable for the interaction term, I use the interaction of my hospital level instrument, natural logarithm of each hospital's county population, and one of my market level instruments, the percentage of a market's population older than 65.

Table 1.5 presents the first stage results which provide evidence of strong correlations between the instruments and the potentially endogenous variables. As expected, there is a positive relationship, significant at the one-percent level, between the natural logarithm of a a hospital's county population and hospital level HHI. Similarly, there is a positive relationship, significant at the one percent level, between the percentage of a market's population over the age of 65 and market level HHI. Also as expected, there is a negative relationship, significant at the one-percent level, between market level HHI and the percentage of a market's population aged 25-29. The interaction of the natural logarithm of each hospital's county population and percentage of market population over the age of 65 is significantly related with the interaction term at the one-percent level. The other three instruments are also significantly related to the interaction term at the one-percent level. The joint F-statistics on the excluded instruments (reported in Table 1.5) for each of the potentially endogeneous variables alleviate concerns about the possibility of weak instruments.

While I expect these geographic characteristics to be correlated with hospital and market level HMO concentration, it is unlikely that the instruments are correlated with the likelihood of receiving C-section, conditional on patients' demographics and diagnoses. One possible concern is that a county's population and the percentage of a population aged of 25-29 could be correlated with a higher volume of births over time both at hospitals within and in markets containing the county. Gruber and Owings (1996) document that C-section rates respond to changes in the volume of births over time.[49] To address this concern, I control for the number of birth discharges at each hospital in each calendar year. Therefore, my instrumental variables will not incorporate the unobserved effect of the volume of births on C-section use.

The instrumental variables estimates for the effects of hospital and market level HHI on C-section likelihood, as opposed to the OLS estimates, are identified by variation in the instrumental variables. Consequently, the identifying variation is from changes in county population and the percentage of a HRA's population aged 25-29 and above 65 over time. Figures 8-10 illustrate the intertemporal variation of the instrumental variables by plotting the distribution of annual changes in each variable. The magnitude of changes in the instruments over time are smaller than the changes in hospital and market level HHI over time. However, there is still sufficient intertemporal variation in the instruments for identification.

[49] Gruber and Owings (1996) argue that as the expected number of births decreases, physicians' expected income decreases. They show that physicians respond by performing more C-sections (as discussed, a more lucrative procedure) to compensate for their expected change in income.

Results

Table 1.2 compares the OLS (column 1) and the instrumental variables results (column 2). The two sets of results of are largely consistent. In both cases, the estimates for the two coefficient interest are statistically significant at the one-percent level with the expected signs. The coefficient estimate for Hospital level HHI is negative and the coefficient estimate for the interaction of hospital and market level HHI is positive. As a falsification test for my instrumental variables, I also estimate this specification on a sample of Kaiser Permanente patients at Kaiser Permanente hospitals, where I should find no significant effects of hospital and market level HHI on C-section likelihood. Both the OLS and 2SLS estimates show no significant effects for the variables of interest on C-sections, as expected.[50]

To answer my first empirical question, I find that C-sections are less likely in hospitals where HMOs are more concentrated. At an average hospital in an average market, a 10% decrease in hospital level HHI would cause a 4.2% increase (0.56 pp) in the likelihood of receiving a C-section (Table 1.2, Panel B). To put the magnitude of this result in context, Gruber et al. (1999) found that a $100 increase physician compensation for C-sections relative to vaginal births would be associated with a 3.9% increase in C-section likelihood.[51] This finding implies that if a hospital contracts with more HMOs (lower concentration), it is predicted to perform more C-sections.

To answer my second empirical question, I find that hospital level HMO concentration has a larger effect on C-section use at hospitals in more competitive (less concentrated) HMO markets. The same 10% decrease in hospital level HHI would cause a 5.9% increase (0.78 pp) in C-sections at a average hospital located in a more competitive market compared to a 3.0% increase (0.40 pp) if the hospital were located in a less competitive market (Table 1.3, Panel C).[52] The level of HMO competition in the market containing the hospital determines the magnitude of the effect of hospital

[50] A more complete discussion of these results is presented in the Appendix, Section A.3.1.

[51] Gruber et al. (1999) estimate the effect of the difference in reimbursement prices for C-sections and vaginal births on C-section use in a sample of Medicaid patients. The magnitude of the effect they estimate implies that a $100 increase in the reimbursement price differential would be associated with a 3.9% increase in C-section use. In their sample, the average difference between the reimbursement prices for C-sections and vaginal births was $127.

[52] As before, in this example a more competitive market is defined as a market with the 25$^{\text{th}}$ percentile of market level HHI. A less competitive market is defined as a market with the 75$^{\text{th}}$ percentile of market level HHI.

level HMO concentration on C-section use.

I find that if a hospital contracts with more HMOs (i.e., lowers its HMO concentration), it is predicted to perform more C-sections. Spillover should represent a greater deterrent to HMOs limiting C-sections at hospitals that contract with more HMOs. This result supports the hypothesis that HMOs are less likely to invest in reducing C-sections at hospitals where spillover undermines their return to investment more. The level of HMO competition in the market, however, determines the magnitude of this effect. It follows that for a given level of hospital level HMO concentration, if the level of HMO competition in the market containing the hospital increases, the number of C-sections performed is also predicted to increase. The implication is that HMO competition can increase the use of C-sections at hospitals that contract with multiple HMOs. Moreover, these results are consistent with the mechanism predicted by my theoretical framework: competition can cause spillover to deter insurers from limiting C-sections, resulting in more C-sections performed.

While my results follow the pattern this story would produce, my interpretation is conditional on two primary assumptions. My empirical analysis is motivated by the theoretical prediction that HMOs have greater spillover concerns at hospitals that contract with more HMOs. This prediction depends on the assumption that spillover occurs. I discuss this first assumption in Section 1.5. Second, I assume that the negative relationship between hospital level HHI and C-sections reflects that spillover deters insurers from limiting C-sections at less concentrated hospitals because of spillover concerns. I discuss this second assumption in Section 1.6.

1.5 Supporting Theoretical, Empirical Assumption: Spillover of HMO Cost Reduction

I find that C-sections are more frequently performed at hospitals with lower HMO concentration. I interpret this result as evidence that C-sections are more prevalent at hospitals where spillover represents a greater deterrent to insurer cost reduction. I use hospital level HMO concentration as a measure of HMO spillover concerns following the prediction from my theoretical framework that an insurer's return on cost reduction is lower at hospitals that contract with more HMOs. Intuitively, if a provider practices similarly for patients of all insurers, any changes in the provider's practice style induced by an individual HMO should affect patients from all insurers treated by that provider. Under this assumption, the degree to which spillover reduces a given HMO's return on investing at a given hospital should therefore be determined by the degree to which that provider contracts with other, competing HMOs. Consequently, both my theoretical and empirical analysis rely on the assumption that hospitals practice similarly for patients of different insurers; I assume that spillover occurs.

To support this assumption, I provide evidence that a single HMO can affect the treatments received by other HMOs' patients. Specifically, I show that the largest HMO at each hospital is able to affect the treatments for patients of other HMOs within the hospital. I do so in two steps: 1) I provide evidence that the largest HMO within a hospital is able to influence whether their patients receive C-sections; 2) I show that other HMO patients within a hospital are treated similarly according to how the top HMO influences whether their own patients receive C-sections.

My findings from the previous section provide evidence that HMOs are able to influence treatments depending on the level of HMO concentration at the hospital and market level. To demonstrate that an individual HMO's influence affects patients of other HMOs, I need to first pick a single HMO within each hospital and show that it is influencing treatments for its own patients. I focus on the HMO with the a largest share of the hospital's patients.

To provide evidence that the largest HMO at each hospital influences the use of C-sections for its patients, I estimate the following variation of Equation (1.4.1) using

OLS. The only difference from my primary specification is that I use HMO Share instead of HHI to measure HMO concentration at the hospital and market level.[53] I estimate the following model of whether patient j with HMO i at hospital h in time t receives a C-section:

$$\begin{aligned} \text{C-section}_{jiht} \;=\; & \beta_0 + \beta_1 \text{HMO Share, hos.}_{iht} + \beta_2 \text{HMO Share, mkt.}_{iht} \\ & + \beta_3 \text{HMO Share, hos.}_{iht} * \text{HMO Share, mkt.}_{iht} \\ & + \beta_4 X_{jt} + \beta_5 H_{ht} + \alpha_h + \alpha_i + \alpha_t + \varepsilon_{jht} \end{aligned} \tag{1.5.1}$$

Here, C-section$_{jiht}$, X_{jt}, and H_{ht} are defined as in Equation (1.4.1). HMO Share, hos.$_{iht}$ refers to HMO i's share of hospital h's HMO birth discharges in year t; HMO Share, mkt.$_{iht}$ refers to HMO i's share of HMO discharges in the market (HRA) containing hospital h in year t. I first want to verify that using HMO Share to measure HMO concentration at the hospital and market level (compared to using HHI) does not influence any conclusions drawn from this test. Table 1.6 shows the baseline results from the previous section (using HHI to measure HMO concentration at the hospital and market level) in Column 1. Column 3 estimates the above equation. Comparing Columns 1 and 3, the results imply the same conclusions for both measures of HMO concentration: there are more C-sections in less concentrated hospitals, and this effect is larger at hospitals located in more competitive (less concentrated) HMO markets.[54]

In Table 1.7, I estimate Equation (1.5.1) but vary the sample. Column 1 uses the baseline sample, Columns 2 limits the sample to only patients of the top HMO at each hospital, and Column 3 limits the sample to patients of all other HMOs at each hospital. For patients of the top HMO at each hospital, the two main coefficient estimates of interest - HMO hospital share and the interaction of HMO hospital and

[53]The goal of this test is to show how one HMO's influence affects patients of other HMOs. I use HMO hospital share to measure spillover risk, as opposed to hospital level HHI. This measure allows the incentive for HMOs to discourage C-sections (or not) to vary by HMO within hospitals. HMO shares vary within hospitals and markets. I cannot estimate this equation using instrumental variables because my instruments for hospital and market level HHI do not vary within hospitals and markets. While it is possible that these estimates are undermined by the endogeneity concerns outlined in Section 1.4.1, my baseline analysis shows that the conclusions drawn from the OLS and 2SLS results are largely consistent.

[54]In less concentrated hospitals, hospital level HMO HHI is lower and on average HMOs control a smaller share of the hospital's birth discharges. Similarly, in more competitive markets HMO HHI is lower and on average HMOs control a smaller share of market discharges.

market share - have the expected signs and are statistically significant at the one-percent level. For patients of other HMOs at the hospital, both coefficient estimates of interest are insignificant (comparing Columns 3). Taken together, these results indicate that at hospitals where the top HMO is larger, their patients receive fewer C-sections. This result is consistent with the notion that the largest HMO at each hospital is more likely to discourage C-sections when they control a larger share of the hospital's discharges. Additionally, the estimates show this effect is larger if the top HMO at a hospital controls a smaller share of their HMO market (when the top HMO at a hospital faces a more competitive market).

I subsequently test whether patients of other HMOs at a hospital exhibit the same practice pattern as patients of the top HMO:

$$\begin{aligned}\text{C-section}_{jiht} \;=\;& \beta_0 + \beta_1 \text{Top HMO Share, hos.}_{ht} + \beta_2 \text{Top HMO Share, mkt.}_{ht} \\ & + \beta_3 \text{Top HMO Share, hos.}_{ht} * \text{Top HMO Share, mkt.}_{ht} \\ & + \beta_4 \text{HMO Share, hos.}_{iht} + \beta_5 \text{HMO Share, mkt.}_{iht} \\ & + \beta_6 \text{HMO Share, hos.}_{iht} * \text{HMO Share, mkt.}_{iht} \\ & + \beta_7 X_{jt} + \beta_8 H_{ht} + \alpha_h + \alpha_i + \alpha_t + \varepsilon_{jht}\end{aligned}$$

Top HMO Share, hos.$_{ht}$ refers to the largest HMO's share of hospital h's HMO birth discharges in year t; Top HMO Share, mkt.$_{ht}$ refers to the share of HMO discharges in the market (HRA) containing hospital h for the largest HMO at hospital h in year t. All of the remaining variables are defined as above. The goal of estimating this specification is to test whether patients of other HMOs are also affected by the top HMO influencing whether their patients receive C-sections. If other HMOs' patients exhibit the same treatment pattern they should receive fewer C-sections at hospitals where the top HMO's hospital share is higher. Also, this effect should be larger when the top HMO faces more competition at the market level. Since it is also possible that other HMOs may try to influence whether their patients receive C-sections analogously to the top HMO, I also control for each patient's HMO's hospital share, market share, and their interaction.

The results are presented in Table 1.8. For comparison, Column 1 shows the effect that the top HMO's hospital share has on its own patients (Column 1 is identical to Column 2 of Table 1.7). Both estimates of the coefficients of interest have the expected signs and are statistically significant at the one percent level. Column 2 of this table shows the relationship between the share of the top HMO at each hospital and C-section use for patients of other HMOs at the hospital. A 10% increase in the top HMO's share at an average hospital in an average market would be associated with a 0.08% decrease (0.01 pp) in the C-section use for patients of *other* HMOs at that hospital.[55] By comparison, the same increase in the top HMO's share results in a 0.11% (0.01 pp) in C-section likelihood for their own patients. Also, in more competitive markets, an increase in the top HMO's hospital share would be associated with a larger decrease in C-section use for other HMOs' patients.

I find that C-sections are less likely for patients of the top HMO when the top HMO has a larger share of hospital discharges. Moreover, this effect is larger in more competitive markets. Table 1.8 shows that both patients from the top HMO and other HMOs at the hospital exhibit this same treatment pattern. Combining these pieces of evidence, the implication is that the top HMO at each hospital is more likely to discourage C-sections for their patients at more concentrated hospitals, and their efforts also affect whether patients from other HMOs receive C-sections at the same hospital. Importantly, this provides evidence that HMO patients are treated similarly within hospitals, despite having different insurers. These results suggest that a single HMO is able to influence the treatments for patients of other HMOs within hospitals. In combination with the arguments and evidence from previous literature that HMOs can affect the treatments of other insurers (for example, see Section 1.1.2), this provides evidence that spillover occurs. This finding supports to the theoretical and empirical assumption underscores my interpretation of the results discussed in the previous section.

[55] Panel B of Table 1.8 shows that the mean share of the top HMO plan at both the hospital and market level is larger for patients of the top HMO than for other patients. The reason is that there are hospital-year observations where the top HMO controls 100% of the discharges. Presumably these HMOs also have large market shares. Because, by definition, patients other than those of the top HMO do not receive treatment at those hospitals, the average share of the top HMO at the hospital and market level is lower for patients of the other HMOs at each hospital.

1.6 Alternative Mechanisms: Why Hospital Level HHI Affects C-Sections Use

The results presented in the Section 1.4 demonstrate that C-sections are more prevalent at hospitals with lower HMO concentration. The results presented in Section 1.5 provide evidence that spillover occurs and, therefore, spillover represents a greater deterrent to HMO cost reduction at hospitals with lower HMO concentration. Taken together, I interpret these results as evidence that spillover concerns at the hospital level inhibit HMOs from limiting C-sections. While my results are consistent with this story, I cannot directly verify it because I can not observe HMO cost reduction. It is possible that other mechanisms may explain the negative relationship between hospital level HMO concentration and C-section use. I therefore consider other potential explanations for this relationship suggested by previous literature. I investigate three main alternative mechanisms - the first I term the “bargaining power argument,” the second I term the “confusion argument,” and the third I term the “public good argument.” I outline each argument to understand what results I would expect if these mechanism were driving the relationship between hospital level HMO concentration and C-section prevalence. I subsequently show that my results are inconsistent with these mechanisms.

1.6.1 The Bargaining Power Argument

HMOs may be better able to influence treatments when they constitute a larger share of a hospital's business. Bundorf et al. (2004) argue that markets with fewer HMOs may exhibit greater response to HMO cost reduction initiatives. For example, providers may be more responsive to a HMO's influence for fear they may lose the business from the HMO's patients if the HMO excludes the provider from their network.[56] If this is the case, HMOs would be more effective at limiting C-section at hospitals with higher HMO concentration because each HMO would control a larger share of the hospital's birth discharges.

[56] This is similar to the argument from Ma and McGuire (2002) as to why HMOs are designed to be effective influencing provider behavior due to their tight control over which providers patients visit.

If this mechanism were driving the negative relationship between hospital level HMO concentration and C-section use, would it also explain why this effect is larger in the more competitive HMO markets? Consider a hospital that contracts with two HMOs (A and B) who each control half of the hospital's birth discharges. Assume HMO B wants to reduce the use of C-sections for their patients. For example, HMO B threatens to remove the hospital from its network if the hospital does not lower its C-section rate. If the hospital's market is only served by HMOs A and B, the hospital would likely be very responsive because they do not want to lose half of their business; there are no outside options for the hospital to contract with if they lose HMO B's patients. However, if the hospital's market is served by ten HMOs ($A, B, ..., J$), the hospital may be less responsive to HMO B's demands. The hospital would be more able to contract with other HMOs to compensate for the lost patients from HMO B. If the negative relationship between hospital level HMO concentration and C-section use is due to the bargaining power mechanism, then it follows that HMOs with larger hospital shares should be more effective at reducing C-sections when HMOs also have larger market shares.

To test this hypothesis, I return to the estimates of Equation (1.5.1) presented in Section 1.5. Column 3 of Table 1.6 shows the effect of a HMO's hospital share on its patients' C-section likelihood and, importantly, how the effect of a HMO's hospital share varies with its market share. Both coefficient estimates of interest - the coefficient estimates for HMO hospital share and its interaction with HMO market share - are statistically significant at the one-percent level. There is a negative relationship between HMOs' hospital share and C-section use for their patients, consistent with the bargaining power story. The coefficient estimate for the interaction term is positive, however, and is not consistent with the bargaining power story. The coefficient estimate for the interaction term implies that the effect of a HMO's hospital share on C-section use is larger when HMOs have a lower market share.[57] This result is the opposite of what I would expect if the negative association between hospital level HMO concentration and C-section use was driven the bargaining power mechanism. While the bargaining power argument could explain a negative relationship

[57] HMO hospital share is negatively related with C-section use. Therefore, the positive coefficient on the interaction term means that the negative, marginal effect of HMO hospital share on C-section likelihood gets smaller in absolute value (towards zero) as HMO market share increases.

between hospital level HMO concentration and C-section use, it cannot explain why this negative effect is larger in more competitive markets.

1.6.2 The Confusion Argument

Another possible, related explanation is that different HMOs use different methods to influence C-section use. Both Hellinger (1996) and Bundorf et al. (2004) argue that insurers may be more effective at influencing providers' practice styles when they control a larger share of a market because the providers may be subjected to a more "homogenous influence on [their] practice patterns" (Bundorf et al., 2004). Extending their argument, if a hospital is less concentrated, HMOs may try many different methods to limit C-sections making the sum of their efforts less effective. As a result, at less concentrated hospitals HMOs may be less effective at reducing C-sections because providers cannot follow all of the different incentives from different HMOs simultaneously.

As Bundorf et al. (2004) argue that this phenomenon could occur at the market level, it should be the case that the hospital level effect of HMO concentration on C-section likelihood should be larger at hospitals located in more concentrated (less competitive) markets. However, the results presented in Section 1.4 support the opposite conclusion. I find that the negative effect of hospital level HMO concentration on C-section likelihood is larger in less concentrated (more competitive) markets.

1.6.3 The Public Good Argument

Spillover of HMO cost reduction represents a public good. Spillover allows all HMOs contracting with a hospital to benefit from one HMO's investment. However, as the number of HMOs at the hospital increases, the number of HMOs potentially contributing to the public good increases. It is possible that as the number of HMOs investing to limit C-sections at the hospital increases, each HMO may by more inclined to free-ride off of other HMOs' investment. Therefore as the number of HMOs increases, they may symmetrically reduce their contributions to the public good (investment in cost reduction). If this were the case, at hospitals that contract with more HMOs, there could be less cost reduction and therefore more C-sections performed.

This mechanism would result in a negative relationship between hospital level HMO concentration and C-section use.

However, if this mechanism were driving the relationship between hospital level HMO concentration and C-sections then this effect should not vary with the level of HMO competition in the market. Because investment in the public good occurs at the hospital level, what happens in the market outside of the hospital should not affect the public good problem. Therefore, holding the number of HMOs at a hospital constant (or the concentration of HMOs), if the level of competition in the market changes there should be no change in the effect of hospital level HMO concentration on C-sections. This mechanism cannot explain the results presented in Section 1.4, which show that the effect of hospital level HMO concentration on C-sections increases with the level of HMO competition in the market containing the hospital.

In all three cases - for the bargaining power, confusion, and public good arguments - the results show that there must be an alternative mechanism driving the effect of hospital level HMO concentration on C-section likelihood. In particular, these arguments cannot explain why this effect empirically varies with level HMO competition in the market containing hospitals. By contrast, the mechanism argued in this study - that competition exacerbates insurers concern about cost reduction spillover - explains why the negative relationship between hospital level HHI and C-section likelihood is larger in more competitive markets.

1.7 Conclusion

I study whether insurer competition can increase health care costs by increasing the prevalence of costly treatments. Insurers have an incentive to limit their reimbursement costs by affecting provider treatment decisions. However, if an insurer encourages a provider to reduce costs, she may also reduce the costs for other insurers who contract with the provider. The degree to which spillover of cost reduction discourages insurers from influencing provider treatment decisions depend on insurers' concern about reducing their rivals' costs. Competition can cause insurers to care about their rivals's cost. I argue that competition increases costly treatments because it causes spillover to discourage insurers from investing in cost reduction.

I specifically investigate the effect of insurer competition on the prevalence of C-sections - a treatment that insurers have a strong incentive to influence. I find that HMO competition can increase C-sections use at hospitals that contract with multiple HMOs. While more work is necessary to determine whether the results of this chapter similarly extend to other treatments, I provide evidence that insurer competition can actually increase the proportion of costly treatments that insurers must reimburse. Further, because I limit my analysis to patients who have low risk of receiving a C-section, as defined by the American College of Obstetricians-Gynecologists, I show that HMO competition is increasing potentially unnecessary C-sections. Unnecessary C-sections can both increase health care costs and lead to worse health outcomes (Johnson and Rehavi, 2016).

In most contexts, competition benefits consumers by forcing firms to reduce their markups through pressuring prices downwards towards firms' marginal costs. While the majority of the previous literature finds that insurer competition reduces premiums, Ho and Lee (2016) show that insurer competition can theoretically increase the reimbursement prices insurers must pay to providers. The mechanism they highlight is that insurer competition decreases individual insurers' bargaining power relative to health care providers within markets; insurer competition allows providers to demand higher reimbursement prices. In this context, I provide empirical evidence of an additional channel through which competition can increase insurer reimbursement costs. If competition increases insurers' marginal costs (their reimbursement costs), it limits insurers' ability to lower premiums (the prices consumers pay for health insurance) and therefore limits the main benefit of competition. As providers continue to consolidate, multiple insurers will be forced to contract with the same providers and these providers will be able to demand higher reimbursement prices. Through the mechanisms argued in this study and by Ho and Lee (2017), in markets with higher hospitals concentration, insurer competition may have a diminished negative effect on premiums and therefore less benefit to consumers. Moreover, it is useful to understand the channels through which insurer competition may have unintended consequences for health care spending and patient outcomes.

A secondary implication of this study is evidence of a causal link between HMO presence within hospitals and the treatments their patients receive. I argue that the results presented in this chapter provide evidence HMOs are effective at influencing the care their patients receive. The results presented in this analysis also suggest that hospitals practice similarly for patients across different insurers. Similar to Maeng et al. (2010), I provide some empirical evidence of spillover of HMO cost reduction. Finally, I provide evidence that HMO insurer competition is a mechanism through which spillover undermines insurer cost reduction. This provides new empirical support to conceptual arguments of Beaulieu et al. (2006), Chernew et al. (2004), and Hellinger (1996) among others.

1.8 Figures

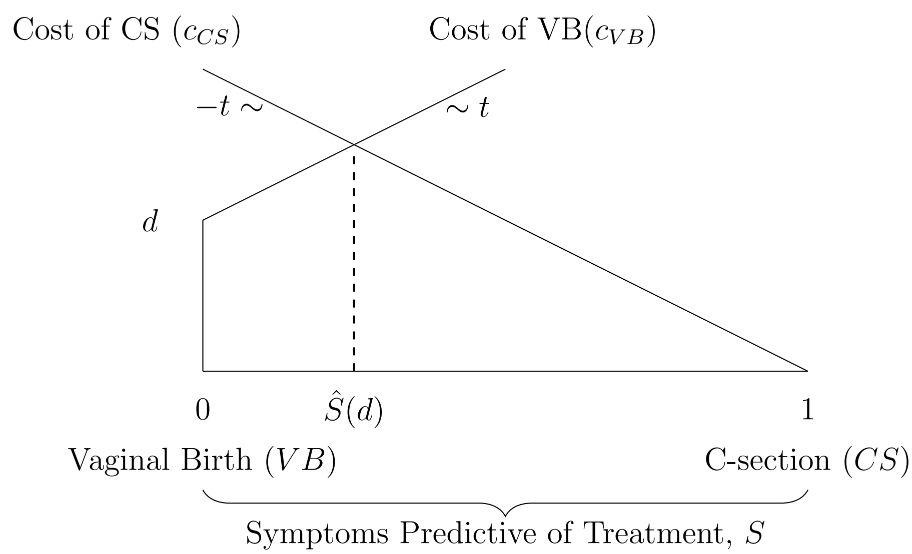


Figure 1.1: Illustration of Hospital Treatment Decision

Notes: Patients are uniformly distributed in their medical symptoms on a Hotelling line from VB to CS. Given medical symptoms, the hospital chooses treatment to minimize the cost of treatment she faces. The solution to the hospital's minimization problem defines a threshold symptom level $\hat{S}(d)$. Importantly, this threshold is an increasing function of the hospital's input cost of performing vaginal births d.

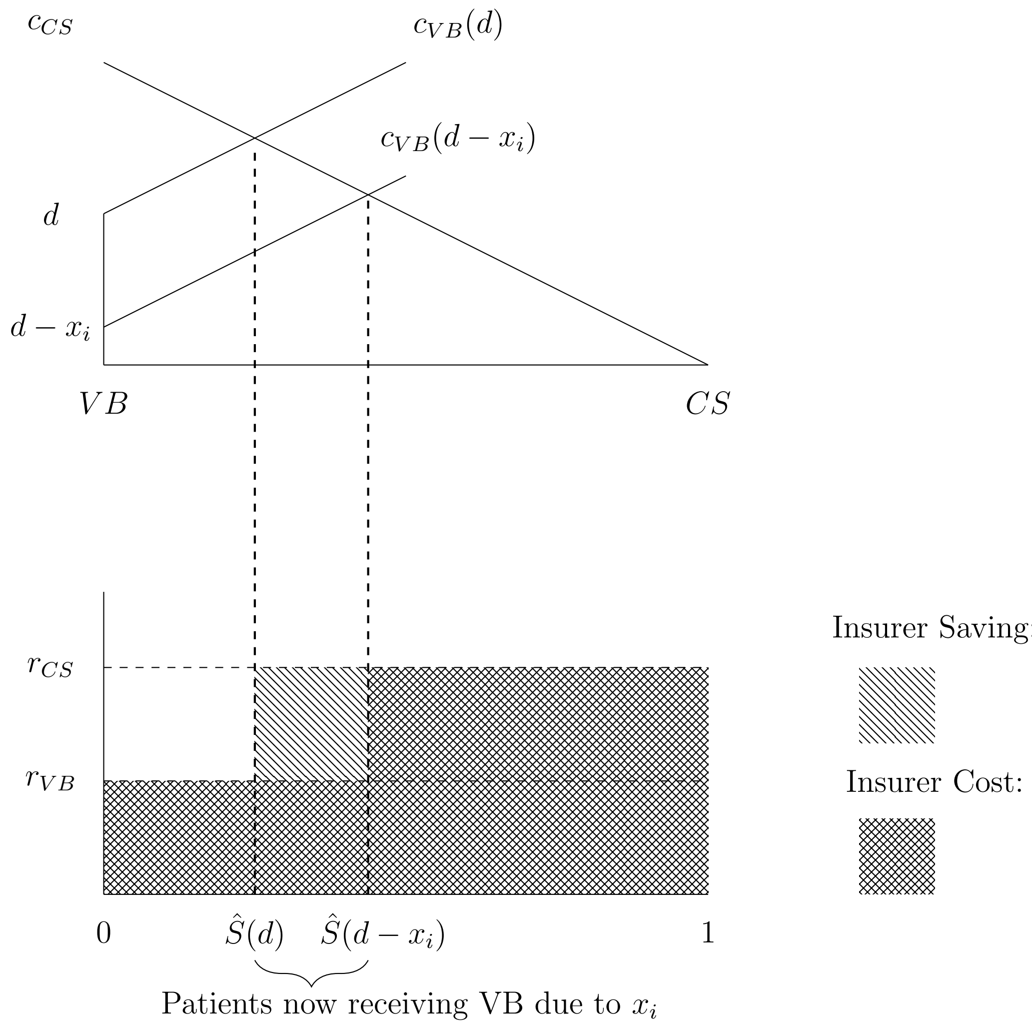


Figure 1.2: Effect of Insurer Investment on Decisions, Insurer Cost

Notes: In the top panel, the insurer i invests x_i to reduce the hospital's input cost of performing vaginal births to $d - x_i$. Because the investment decreases the hospital's cost of performing vaginal births, it increases the percentage of vaginal births performed ($\hat{S}$), and decrease the percentage of C-sections ($1 - \hat{S}$).

The bottom panel illustrates insurer i's expected cost per-patient. This is calculated by summing the product of the probabilities that a patient receives each treatment and the reimbursement insurer i must pay for each treatment: $r_{VB} * \hat{S} + r_{CS} * (1 - \hat{S})$. By investing x_i, the insurer reduces the cost she must pay because she reduces the number of C-sections. Her cost reduction is equal to the product of the percentage of people who now receive vaginal births instead of C-sections ($\hat{S}(d - x_i) - \hat{S}(d)$) and the difference in reimbursement rates ($r_{CS} - r_{VB}$). This is visually represented by the box labeled insurer saving.

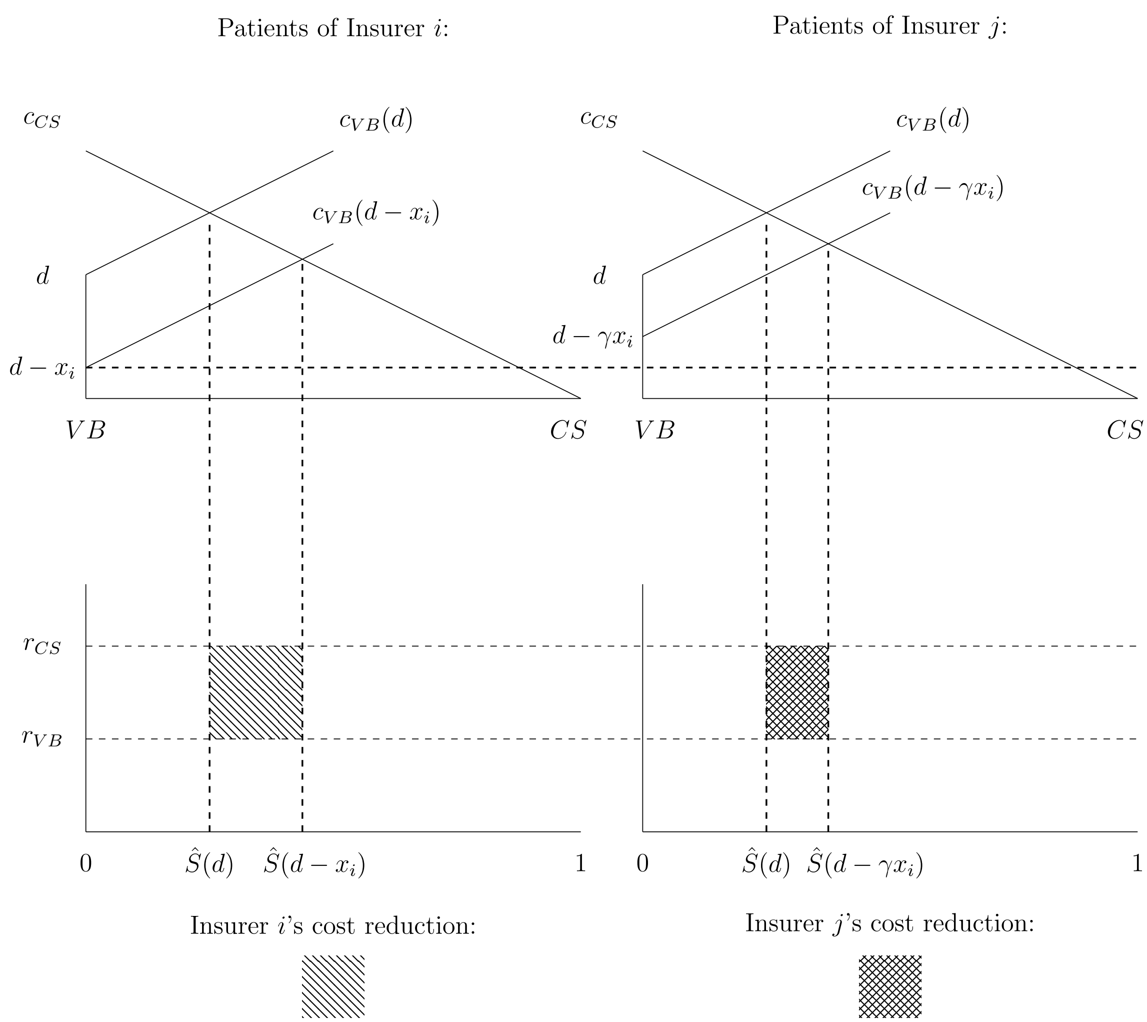


Figure 1.3: Illustration of Insurer Investment Spillover

Notes: This figure illustrates an example where there are two insurers (i and j) operating in the market and contracting with the hospital. In the top panel, as in Figure 2, insurer i invests x_i to reduce the hospital's input cost of vaginal births to $d - x_i$ for their patients. However, insurer i also reduces the hospital's input cost of vaginal births for patients of insurer j's by γx_i due to spillover. The bottom panel illustrates how insurer i's investment reduces insurer j's expected cost per-patient in addition to reducing their own.

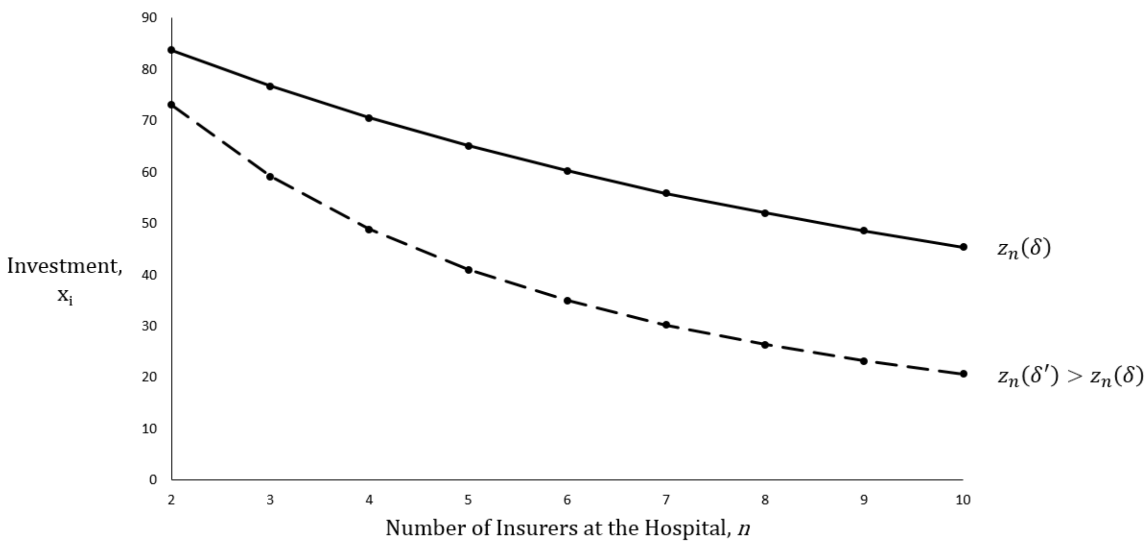


Figure 1.4: Effect of the Number of Insurers on Investment

Notes: This figure plots insurer i's optimal choice of investment as a function of the number of insurers, n. I vary n for two different values of δ. I set the reimbursement prices (r_{CS}, r_{VB}) as the average physician reimbursements for the respective procedures from Foo et al. (2017). The other cost parameters (t,d, ν) are set to satisfy the second order condition, ensure $\hat{S} \in$[0,1], and illustrate the comparative statics of the model. The parameters defining the demand coefficients are similarly set to satisfy the assumptions set forth by Vives (1999), to ensure that patients find it optimal to buy positive quantities of insurance, and illustrate the comparative statics of the model.

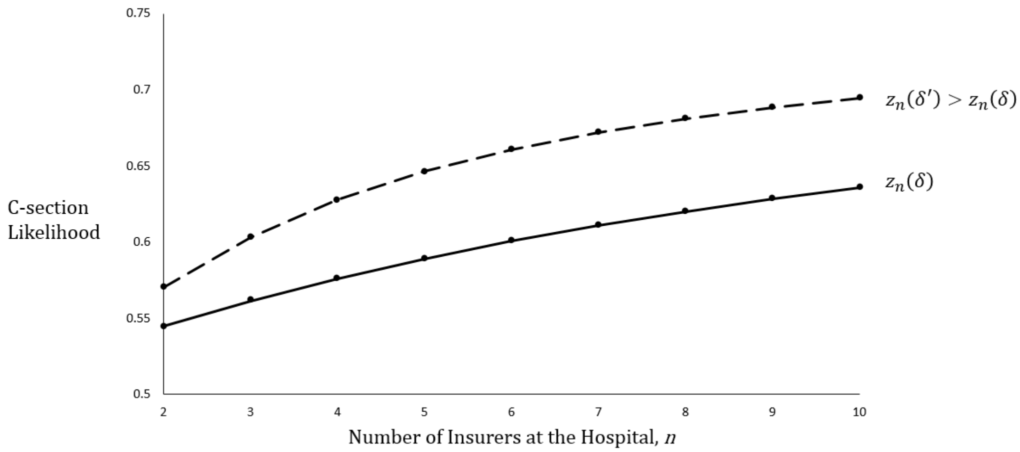
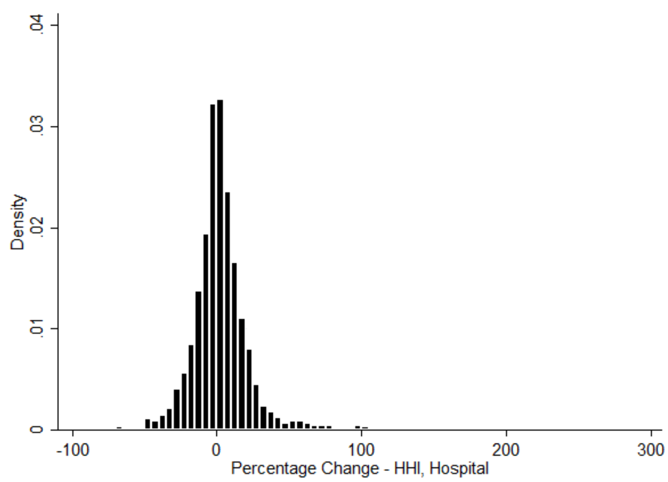


Figure 1.5: Effect of the Number of Insurers on C-Section Likelihood

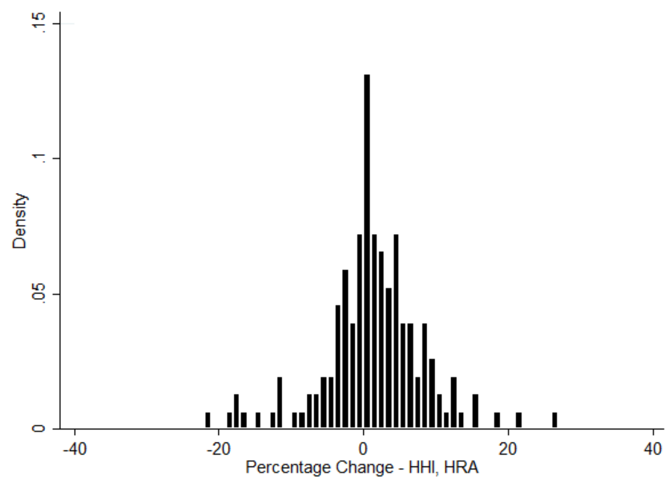
Notes: This figure plots the percentage of C-sections performed derived from the theoretical model as a function of the number of insurers, n. I vary n for two different values of δ. The parameters of the model are set as in Figure 4.

Figure 1.6: Distribution of Annual Changes (%) - Hospital Level HMO HHI



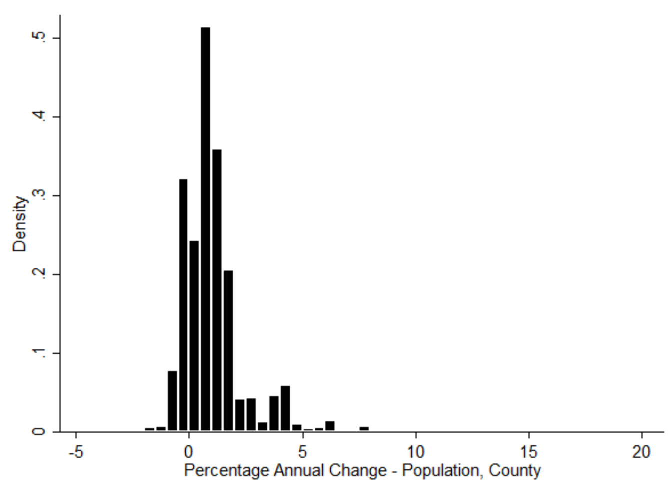
Notes: This histogram presents the distribution of annual changes in hospital level HMO HHI for sample California hospitals from 2005-2013 (bin size = 5.0%). Hospital level HMO HHI is computed as described in Appendix A.2.3 using data from the California Office of Statewide Health Planning and Development (OSHPD) discharge data, 2005-2013.

Figure 1.7: Distribution of Annual Changes (%) - Mkt.(HRA) Level HMO HHI



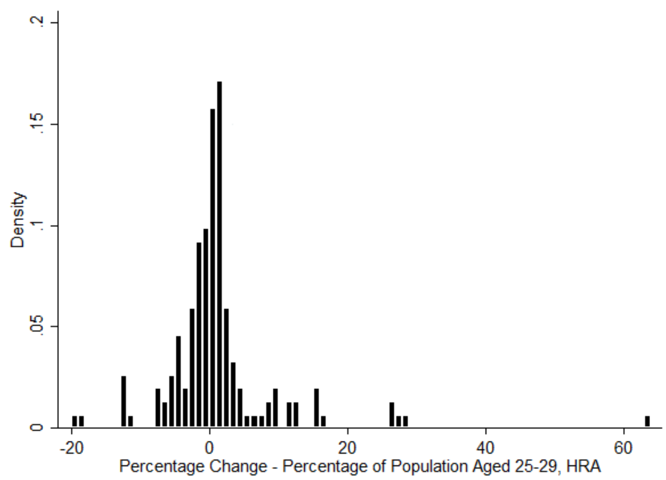
Notes: This histogram presents the distribution of annual changes in market level HMO HHI for sample California Health Insurance Rating Areas (HRA) from 2005-2013 (bin size = 1.0%). Market (HRA) level HMO HHI is computed as described in Appendix A.2.3 using data from the OSHPD discharge data, 2005-2013.

Figure 1.8: Distribution of Annual Changes (%) - Population, County



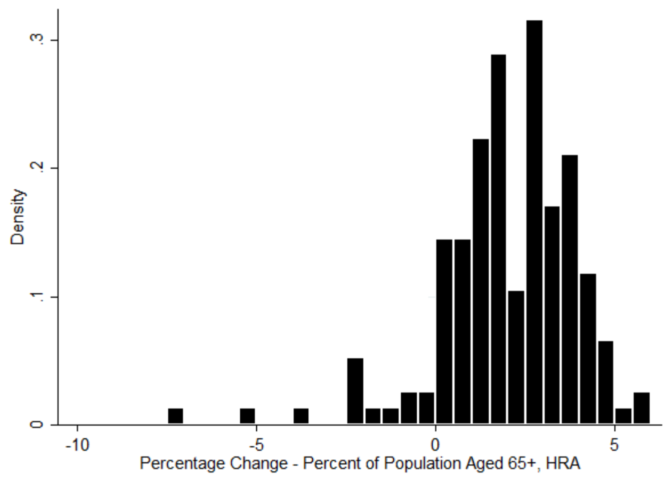
Notes: This histogram presents the distribution of annual changes in county population for sample California counties from 2005-2013 (bin size = 1.0%). Percentage changes in county population are computed using annual population estimates from the American Community Survey, 2005-2013.

Figure 1.9: Distribution of Annual Changes (%) - Percentage Pop. Aged 25-29, HRA



Notes: This histogram presents the distribution of annual changes in county population for sample California counties from 2005-2013 (bin size = 0.5%). Percentage changes in the percentage of a Health Insurance Rating Area's (HRA) population aged 25-29 are computed using ACS annual population estimates, 2005-2013. I compute HRA level demographic data using the county level ACS data as described in Appendix A.2.3.

Figure 1.10: Distribution of Annual Changes (%) - Percentage Pop. Aged 65+, HRA



Notes: This histogram presents the distribution of annual changes in county population for sample California counties from 2005-2013 (bin size = 0.5%). Percentage changes in the percentage of a Health Insurance Rating Area's (HRA) population aged over 65 are computed using ACS annual population estimates, 2005-2013. I compute HRA level demographic data using the county level ACS data as described in Appendix A.2.3.

1.9 Tables

Table 1.1: Descriptive Statistics

Variable	All HMO Patients Mean	All HMO Patients Std. Dev.	Low-Risk Patients Mean	Low-Risk Patients Std. Dev.	Baseline Sample Mean	Baseline Sample Std. Dev.
C-Section	0.316	0.465	0.128	0.335	0.132	0.339
Low Risk	0.621	0.485	—	—	—	—
Cord Prolapse	0.002	0.042	0.001	0.038	0.002	0.040
Dystocia	0.166	0.372	0.092	0.289	0.093	0.290
Fetal Distress	0.002	0.050	0.003	0.050	0.002	0.044
Herpes	0.020	0.140	0.020	0.140	0.015	0.122
Maternal Distress	0.000	0.014	0.000	0.013	0.000	0.013
Previa	0.007	0.083	0.005	0.067	0.004	0.064
Age	28.394	6.114	27.600	6.004	27.353	6.121
Asian	0.147	0.353	0.143	0.350	0.136	0.341
Black	0.087	0.282	0.082	0.275	0.083	0.276
Native-American/Eskimo/Aluet	0.004	0.065	0.004	0.063	0.004	0.066
Other, Non-White	0.206	0.404	0.205	0.404	0.182	0.386
White	0.557	0.497	0.566	0.496	0.593	0.492
Hispanic	0.409	0.492	0.411	0.492	0.411	0.492
Kaiser	0.320	0.467	0.316	0.465	—	—
Medi-Cal	0.336	0.472	0.340	0.474	0.426	0.494
Medi-Cal, COHS	0.053	0.225	0.055	0.228	—	—
Plan Share, Hospital	0.527	0.371	0.524	0.370	0.315	0.243
Plan Share, Market (HRA)	0.233	0.168	0.233	0.168	0.154	0.121
HHI, Hospital	0.519	0.339	0.516	0.338	0.311	0.185
HHI, Market (HRA)	0.218	0.071	0.217	0.071	0.208	0.064
Observations	1,904,600		1,183,704		736,403	

Notes: All data is from the California OSHPD discharge data from 2005-2013. All statistics are rounded to three digits. This analysis only includes patients between the ages of 16-42 and at hospitals with more than 100 birth discharges in a calendar year. I exclude patients missing demographic, diagnostic, or insurance information. HMO Patients refers to all patients who have Knox-Knee regulated insurance plans; For a more complete discussion see Section A.2.1 in the Data Appendix. The baseline sample also excludes high risk patients, patients with Kaiser Permanente insurance, patients at Kaiser Permanente Medical Centers, and patients with insurers that do not compete with commercial insurers. Both hospital and market level plan share are only reported for patients of commercial HMO plans, excluding patients from Medi-Cal HMOs operating in COHS (County Organized Health System) counties. Further, HHI only sums the squares of shares for commercial HMO plans and Medi-Cal HMO plans that are operated by or directly compete with a plan operated by a commercial insurer.

Table 1.2: Effect of Hospital and Market level HHI on C-Section Use - OLS and 2SLS

Panel A: Baseline Results

Estimator:	OLS		2SLS	
Sample:	Baseline	Including High Risk	Baseline	Including High Risk
Dependent Variable:	C-Section	C-Section	C-Section	C-Section
Variables:	(1)	(2)	(3)	(4)
HHI, Hospital	-0.065***	-0.042***	-0.491***	-0.252**
	(0.016)	(0.014)	(0.144)	(0.127)
HHI, Market (HRA)	-0.003	0.013	-0.451***	-0.184
	(0.033)	(0.029)	(0.165)	(0.148)
HHI, Hospital x HHI, Market (HRA)	0.204***	0.145***	1.497***	0.499
	(0.064)	(0.057)	(0.554)	(0.495)
Medi-Cal Patient	-0.017***	-0.021***	-0.017***	-0.021***
	(0.001)	(0.001)	(0.001)	(0.001)
Hospital Controls	X	X	X	X
Labor Complication, Patient Demographic Controls	X	X	X	X
Low Risk Controls		X		X
Hospital, Insurer, Year FE	X	X	X	X
Number of Observations	736,403	1,180,347	736,403	1,180,347
Adj. R^2	0.302	0.546	0.302	0.546

Panel B: Marginal Effect of 10% Decrease in Hospital Level HHI on C-Section Likelihood, at an Avg. Hospital in Avg. Market

Marginal Effect (%)	0.520	0.110	4.232	1.378
Marginal Effect (pp)	0.069	0.037	0.559	0.460
C-Section - Mean	0.132	0.334	0.132	0.334
HHI, Hospital - Mean	0.311	0.312	0.311	0.312
HHI, Market(HRA) - Mean	0.208	0.209	0.208	0.209

Notes: All patient, insurer data is from the California OSHPD discharge data, 2005-2013. County and HRA population and age demographics are from the American Community Survey (ACS). Columns 3-4 are estimated using 2SLS; Table 1.5 presents the first stage results for column 3. Instruments for hospital and market level HHI and their interaction: natural logarithm of the population of hospital's county; percentage of population aged 25-29, $>$ 65 in hospital's HRA, and the interaction of the natural logarithm of the population of a hospital's county and the percentage of a hospital's HRA aged $>$ 65. Demographic controls: age, race/ethnicity (Asian, Black, Native American/Eskimo/Aleut, Other Non-White; Hispanic); indicator for whether patients are part of a local initiative in a Two Plan market or Geographic Managed Care Medi-Cal only HMO plan. Labor complication controls: cord prolapse, dystocia, fetal/maternal distress, herpes and previa. Low risk controls: diabetes, hypertension, malpresentation, multiple gestation, not full term, obstructed labor, and previous C-section. Hospital Controls: the number of hospitals in each hospital's county and the natural logarithm of the number of birth discharges for each hospital in the calendar year. Note: hospital level HHI is the HHI of HMO birth discharges at the hospital and market level HHI is the HHI of all HMO discharges in the hospital's market (HRA). Standard errors are reported in parentheses; statistical significance denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All coefficients and standard errors are rounded to three digits. The marginal effect of an decrease in hospital level HHI is computed as the product of the magnitude of the decrease (10% increase from the mean) and the sum of the HHI, Hospital coefficient and the product of the coefficient on the interaction term and mean market level HHI. The marginal effects are reported as percents out of 100 to facilitate interpretation.

Table 1.3: Interpreting Results - Effect of a Decrease in Hospital Level HHI on C-Sections

Panel A: Relevant Descriptive Statistics

C - Section, Mean	0.134
HHI, Hospital - Mean	0.311
HHI, Market (HRA), 25^{th} Percentile	0.163
HHI, Market (HRA), 50^{th} Percentile	0.173
HHI, Market (HRA), 75^{th} Percentile	0.243

Panel B: OLS Results, Baseline Sample
Effect of 10 % Decrease in Hospital Level HHI on C-Section Use at an Avg. Hospital, by Market Type

Insurer Competition, Market (HRA)	HHI, Market (HRA)	Effect of Decrease (%)	Effect of Decrease (pp)
Higher	25^{th} Percentile	0.746	0.099
Median	50^{th} Percentile	0.693	0.092
Lower	75^{th} Percentile	0.356	0.047

Panel C: 2SLS Results, Baseline Sample
Effect of 10 % Decrease in Hospital Level HHI on C-Section Use at an Avg. Hospital, by Market Type

Insurer Competition, Market (HRA)	HHI, Market (HRA)	Effect of Decrease (%)	Effect of Decrease (pp)
Higher	25^{th} Percentile	5.895	0.780
Median	50^{th} Percentile	5.503	0.728
Lower	75^{th} Percentile	3.037	0.402

Notes: Descriptive statistics are from California OSHPD discharge data, 2005-2013. The marginal effects are computed using the results of Table 3, Column 1 for the OLS results and Column 3 for the 2SLS results. The marginal effects of an increase in hospital level HHI computed as the product of the magnitude of the decrease (10% decrease from the mean) and the sum of the Hospital, HHI coefficient and the product of the coefficient on the interaction term multiplied and the market level HHI measure listed in Column 2. Marginal effects (%) are reported as percents out of 100 to facilitate interpretation in Column 3 and percentage points (pp) in Column 4.

Table 1.4: Robustness Tests for Baseline Specification: Clustering Standard Errors, Varying Market Definitions

Robustness Exercise:	Baseline	Clustering Standard Errors	Varying Market Definition		
Market Definition	HRA	HRA	HRA	HRR	County
Dependent Variable:	C-Section	C-Section	C-Section	C-Section	C-section
Variables:	(1)	(2)	(3)	(4)	(5)
HHI, Hospital	-0.065***	-0.065*	-0.065***	-0.078***	-0.035***
	(0.016)	(0.034)	(0.016)	(0.014)	(0.012)
HHI, Market	-0.003	-0.003	-0.002	-0.040	-0.061*
	(0.033)	(0.070)	(0.033)	(0.033)	(0.029)
HHI, Hospital x	0.204***	0.204*	0.207***	0.246***	0.043
HHI, Market	(0.064)	(0.121)	(0.064)	(0.053)	(0.039)
Hospital Controls	X	X	X	X	X
Labor Complication, Patient Demographic Controls	X	X	X	X	X
Hospital, Insurer, Year FE	X	X	X	X	X
Standard Errors Clustered at Hospital Level		X			
Include Non-Contiguous HRAs?	X	X		—	—
Number of Observations	736,403	736,403	732,388	736,403	736,403
R^2	0.302	0.303	0.303	0.303	0.303

Notes: All patient, insurer data is from the California OSHPD discharge data, 2005-2013. All control variables defined as in Table 1.2. In columns 1-3, I define a HMO market as a Health Insurance Rating Area (HRA). In column 4, I define a HMO market as a Hospital Referral Region according to the Dartmouth Atlas. In column 5, I define a HMO market as a county. In column 3, I omit observations from HRAs that are non-contiguous. In Column 2 I cluster standard errors at the hospital level (230 clusters). Standard errors are reported in parentheses; statistical significance denoted as follows: *** p < 0.01, ** p < 0.05, * p < 0.10. All coefficients and standard errors are rounded to three digits.

Table 1.5: Baseline 2SLS Specification - First Stage Results

Sample:	Baseline	Baseline	Baseline
Dependent Variable:	HHI, Hospital	HHI, Market	HHI, Hospital x HHI, Market
Variables:	(1)	(2)	(3)
log(Population), County	0.193***	0.189***	0.093***
	(0.006)	(0.002)	(0.002)
% of Pop. Aged 25-29, HRA	-0.127***	-0.385***	-0.052***
	(0.014)	(0.004)	(0.004)
% of Pop. Aged > 65, HRA	6.001***	9.050***	5.335***
	(0.208)	(0.054)	(0.060)
log(Population), County x % of Pop. Aged > 65, HRA	-0.037***	-0.612***	-0.266***
	(0.015)	(0.004)	(0.004)
Medi-Cal Patient	0.002***	0.000	0.001***
	(0.000)	(0.000)	(0.000)
Hospital Controls	X	X	X
Labor Complication Controls	X	X	X
Patient Demographic Controls	X	X	X
Hospital, Insurer, Year FE	X	X	X
Number of Observations	736,403	736,403	736,403
Adj. R^2	0.897	0.943	0.917
F - Statistic	22,507.76	42,969.23	28,560.81

Notes: All patient and insurer data is from the California OSHPD discharge data, 2005-2013. County and HRA population and age demographics are from the ACS. All control variables defined as in Table 1.2. Standard errors are reported in parentheses; statistical significance denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All coefficients and standard errors are rounded to three digits. I report the joint F-statistic of the excluded instruments for each of the first stage regressions.

Table 1.6: Varying the Measure of HMO Concentration

Panel A: OLS Results, Changing Concentration Measure			
Empirical Measure, HMO Concentration (Hospital):	HHI	HMO Share	HMO Share
Empirical Measure, HMO Concentration (Market):	HHI	HHI	HMO Share
Dependent Variable:	C-Section	C-Section	C-Section
Variables:	(1)	(2)	(3)
HMO Concentration, Hospital	-0.065***	-0.021***	-0.024***
	(0.016)	(0.008)	(0.004)
HMO Concentration, Market	-0.003	0.043*	-0.025**
	(0.036)	(0.024)	(0.010)
HMO Concentration, Hospital x HMO Concentration, Market	0.204***	0.065**	0.085***
	(0.064)	(0.031)	(0.016)
Hospital Controls	X	X	X
Labor Complication Controls	X	X	X
Patient Demographic Controls	X	X	X
Hospital, Insurer, Year FE	X	X	X
Number of Observations	736,403	736,403	736,403
Adj. R^2	0.302	0.303	0.303
Panel B: Marginal Effect of 10% Decrease in Hospital Level HMO Concentraton on C-Section Likelihood, at an Avg. Hospital in an Avg. Market			
Marginal Effect (%)	0.456	0.185	0.258
Marginal Effect (pp)	0.069	0.024	0.034
C-Section Mean	0.132	0.132	0.132
HMO Concentration, Hospital - Mean	0.311	0.311	0.315
HMO Competition, Market - Mean	0.208	0.208	0.154

Notes: All patient and insurer data is from the California OSHPD discharge data, 2005-2013. All control variables defined as in Table 1.2. Hospital level HMO share is of HMO birth discharges for each hospital in each calendar year. Market level HMO share is of all HMO discharges in each market in each year. All specifications use the baseline sample as previously defined. Standard errors are reported in parentheses; statistical significance denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All coefficients and standard errors are rounded to three digits. The marginal effects are computed as before.

Table 1.7: Effect of Plan Share on C-Section Likelihood - Top HMO's Patients vs. Other

Sample:	Baseline	Top HMO	Other HMO
Dependent Variable	C-Section	C-Section	C-Section
Variables:	(1)	(2)	(3)
HMO Share, Hospital	-0.024***	-0.061***	0.002
	(0.004)	(0.010)	(0.011)
HMO Share, Market (HRA)	-0.025**	-0.146***	-0.008
	(0.010)	(0.030)	(0.019)
HMO Share, Hospital x	0.085***	0.253***	-0.051
HMO Share, Market (HRA)	(0.016)	(0.039)	(0.081)
Medi-Cal Patient	-0.016***	-0.019***	-0.014***
	(0.001)	(0.002)	(0.002)
Hospital Controls	X	X	X
Labor Complication Controls	X	X	X
Patient Demographic Controls	X	X	X
Hospital, Insurer, Year FE	X	X	X
Number of Observations	736,403	323,169	413,234
Adj. R^2	0.302	0.312	0.296

Notes: All patient and insurer data is from the California OSHPD discharge data, 2005-2013. All control variables defined as in Table 1.2. Note: hospital and market level HMO share are computed as before. All columns test the same specification, but vary the samples. Column 1 tests the baseline sample, Column 2 restricts to only patients from the largest HMO at each hospital, and Column 3 tests all patients except for the patients of the largest insurer at each hospital. Note: Column 1 is identical to Column 1 of Table 1.6. Standard errors are reported in parentheses; statistical significance denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All coefficients and standard errors are rounded to three digits.

Table 1.8: Effect of Top HMO Share on C-Section Likelihood by Patients' Insurer

Panel A: Regression Results

Sample:	Top HMO	Other HMO
Dependent Variable	C-Section	C-Section
Variables:	(1)	(2)
Top HMO Share, Hospital	-0.061***	-0.049***
	(0.010)	(0.012)
Top HMO Share, Market (HRA)	-0.146***	-0.119***
	(0.030)	(0.021)
Top HMO Share, Hospital x	0.253***	0.250***
Top HMO Share, Market (HRA)	(0.040)	(0.020)
HMO Share, Hospital	—	-0.003
		(0.011)
HMO Share, Market (HRA)	—	-0.025
		(0.020)
HMO Share, Hospital x	—	0.049
HMO Share, Market (HRA)		(0.084)
Hospital Controls	X	X
Patient Demographic, Labor Complication Controls	X	X
Year, Hospital, Insurer FE	X	X
Number of Observations	323,169	413,234
Adj. R^2	0.312	0.297

Panel B: Marginal Effect of 10% Decrease in Top HMO Share on C-Section Likelihood, at an Avg. Hospital in an Avg. Market (HRA)

Marginal Effect (%)	0.113	0.083
Marginal Effect (pp)	0.014	0.011
C-Section - Mean	0.125	0.138
Top HMO Share, Hospital - Mean	0.527	0.380
Top HMO Share, Market (HRA) - Mean	0.255	0.183

Notes: All patient and insurer data is from the California OSHPD discharge data, 2005-2013. All control variables defined as in Table 1.2. Standard errors are reported in parentheses; statistical significance denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All coefficients and standard errors are rounded to three digits. The marginal effects are computed as before.

Chapter 2

Does Hospital-Physician Integration Affect Patient Treatments?

Prior to the 1990s, hospitals and physicians were, for the most part, separate entities. By 2012 over 45% of U.S. hospitals participated in some form of physician integration through either contracting with or acquiring physician practices (Figure 2.1). Recently, there has been a rise in hospital ownership of physician practices and a corresponding decline in hospitals engaging in contractual relationships with physician practices.[1] It is unclear whether certain forms of hospital physician integration increase efficiency or raise anti-competitive concerns. Hospital-physician integration historically has not received the same antitrust review as horizontal consolidation, for example, between hospitals (Gaynor, 2006). The concern is that integration could allow affiliated hospitals and physicians to accumulate larger market shares and consequently increase the prices they charge payers. Previous studies find evidence of an association between some forms of hospital-physician integration (ownership forms of integration) and increased hospital prices and health care spending (Baker et al., 2014; Cuellar and Gertler, 2006; Koch et al., 2017; Neprash et al., 2015). On the other hand, there is little empirical evidence to date that any forms of hospital-physician

[1] As seen in Figure 2.1, according to the American Hospital Association Annual Survey data from 2005 to 2012, the proportion of integrated hospitals in the U.S. has remained relatively constant. However, there has been a dramatic shift from contractual forms to ownership forms of integration.

integration could enable more efficient care delivery and lower health care utilization. Whether hospital-physician integration affects utilization, and whether the form of integration matters, remain open, empirical questions.

I investigate whether hospital-physician integration alters the treatments patient receive. Most previous studies of the effect of integration on utilization focus on outcomes that measures how much care patients use (Baker et al., 2014; Cuellar and Gertler, 2006; Neprash et al., 2014).[2] I study the use of a specific treatment which allows me to examine whether hospital-physician integration also affects utilization by influencing what type of care patients receive. Madison (2004) uses a similar approach to study the effect of integration on a specific clinical setting: treatment of Medicare patients with Acute Myocardial Infarction (AMI). As noted by Gaynor (2006), it is plausible that integration may have different effects in different geographic and patient markets. To that end, I contribute to the literature by studying the effect of integration on utilization in a different patient population - privately insured patients - and different treatment setting.

I estimate the effect of hospital-physician integration on Cesarean section (C-section) use in childbirth using a sample of privately insured patients from California over 2005-2012.[3] Childbirth is a convenient treatment setting to study utilization because it presents a binary choice between a high intensity, high cost procedure (C-section) and a comparatively low intensity, low cost alternative (vaginal birth). Moreover, C-sections are a treatment found by economic literature to respond to changes in health care provider incentives. I primarily use hospital discharge data from California's Office of Statewide Health Planning and Development (OSHPD). I supplement the OSHPD data with data on hospital-physician arrangements from the American Hospital Association Annual Survey.

I am able to decompose the effect of hospital-physician integration on C-section use by the form of integration. I exploit heterogeneity in the various forms hospital-

[2] Baker et al. (2014) find no evidence that hospital-physician integration increased admissions per-enrollee. Cuellar and Gertler (2006) did not find any consistent evidence that integration affected aggregate procedure use. Their measure aggregates the utilization rates of three common procedures: Cesarean sections, incidental appendectomy in the elderly, and bi-lateral cardiac catheterization. Neprash et al. (2015) find that integration had no significant effect on price standardized spending per-enrollee in inpatient settings.

[3] Ciliberto and Dranove (2006) argue that California is a particularly good setting for this type of analysis because "it has been a leader in innovative health care organizational practices."

physician integration to investigate whether particular characteristics of integration affect the use of C-sections. This allows me to consider mechanisms suggested by previous literature through which integration could impact the use of C-sections. I include hospital fixed effects to account for time-invariant unobservable hospital characteristics that may bias my estimates. For example, it could be the case a hospital with unobservable preferences for lower costs could be less likely to perform C-sections and more likely to integrate with physician practices. I also include a rich set of hospital and patient characteristics to account for time varying characteristics that may be correlated with both integration and C-section use. My estimates assume that changes in unobservable hospital, patient, and physician characteristics are uncorrelated with the decision to perform C-sections.[4]

I find that there is a significant, negative association between hospital-physician integration and C-section use. C-sections are 2% less likely at integrated hospitals than at hospitals with no physician affiliations. This result is similar in magnitude to the effect of a $100 change in physician compensation for performing C-sections.[5] The negative effect of hospital-physician integration on C-section use is persistent across contractual and ownership forms of integration. This result is consistent with the conceptual argument of Cuellar and Gertler (2006) that integrated hospitals are better able to coordinate care delivery, monitor care delivery, or both. This finding complements previous findings that looser forms of hospital-physician integration, in particular contractual forms of integration, are not associated with increased hospital prices and health care spending. Along with Baker et al. (2014), I provide some evidence that contractual forms of hospital-physician integration may be socially beneficial.

[4]This assumption is common to similar, previous studies (namely, Baker et al., 2014; Ciliberto (2006); Ciliberto and Dranove, 2006; Cuellar and Gertler, 2006; Madison, 2004; Koch et al., 2017).

[5]Gruber et al. (1999) find that a $100 change in difference between the physician reimbursement prices for C-section and vaginal birth would be associated with a 3.9% change in C-section rates for Medicaid patients. To provide further context, in their sample the average reimbursement price differential is $127.

2.1 Background: Hospital-Physician Integration and Utilization

2.1.1 Forms of Hospital-Physician Integration

In the 1990s and in the early 2000s, hospitals and physicians began integrating through both contractual relationships and by hospitals acquiring ownership of physician practices (Ciliberto and Dranove, 2006; Kocher and Sahni, 2011).[6] Recently, there has been an increase in hospital ownership of physician practices and a decline in hospitals contracting with physician practices. Koch et al. (2007) note that this increase in hospital ownership of physician practices is primarily attributable to a combination of mergers between hospitals and physician practices and shifts in physician employment preferences.[7] Hospital-Physician integration can take many forms. I study four common forms of hospital-physician arrangements: Independent Practice Associations (IPAs), Physician-Hospital Organizations (PHOs), Integrated Salary Models (ISMs), and Medical Foundations (MFs).[8]

In order to discuss how different forms of hospital-physician integration can affect utilization, it is helpful to understand some of the characteristics of the different

[6]As noted by both Ciliberto and Dranove (2006) and Kocher and Sahni (2011), towards the end of the 1990s, many hospital and physician arrangements dissolved. However, in recent years the trend of hospital-physician integration has re-emerged (Kocher and Sahni, 2011).

[7]The primary hypothesis is that health care provider (both hospital and physician) consolidation is driven to providers' desire to accumulate market power in order to charge payers higher prices (Cooper et al., 2015). It is possible that this also is the primary reason motivation hospitals to contract with and to acquire physician practices (Gaynor, 2006). Kocher and Sahndi (2011) mention that physicians may "value better work-life balance and [may be] more willing than preceding generations to trade higher incomes for the lifestyle flexibility and administrative simplicity provided by hospital employment."

[8]Following previous literature (namely, Ciliberto and Dranove, 2006; Cuellar and Gertler, 2006; Madison, 2004), I group together Open PHOs (OPHOs), Closed PHOs (CPHOs) and Management Service Organizations (MSOs) as Physician Hospital Organizations. Ciliberto and Dranove (2006) mention that they "are unaware of any practical differences in the operations of OPHOs and CPHOs," but do not include MSOs in their analysis. Madison (2004) similarly groups together OPHOs and CPHOs, but does not include MSOs. Cuellar and Gertler (2006) group together CPHOs and MSOs, but treat OPHOs as separate. In summary, among these three forms of hospital-physician integration, multiple studies document their qualitative similarities and none of these studies document any statistical differences in their effects on hospital prices, health care spending, or treatment decisions.

forms of hospital-physician integration. While the various forms of hospital-physician integration differ in their level of administrative, financial, and legal integration, each form is more integrated than a hospital with no physician affiliations. Non-affiliated hospitals and physicians hold separate contracts with payers (namely, managed care organizations) and do not collaborate on administrative services or care coordination (Bazzoli et al., 2000). IPAs are widely considered the loosest form of hospital-physician integration. Compared to non-affiliated hospitals and physicians, IPAs primarily help physicians contract with managed care plans (Bazzoli et al., 2000; Baker et al., 2014). PHOs are joint-ventures between physicians and hospitals that can additionally provide administrative services and some coordination of care (Baker et al., 2014; Ciliberto and Dranove, 2006; Cuellar and Gertler, 2006).

In both IPAs and PHOs, hospitals contract with physicians who still own their practices. By contrast, in ISMs and MFs the hospitals own the physician practices (Bazzoli et al., 2000). For this reason, following Bazzoli et al. (2000), forms of hospital-physician integration are often broken into two groups: contractual forms of integration (IPAs and PHOs) and ownership forms of integration (ISMs and MFs). Distinct from contractual forms, in ISMs and MFs physicians are employed and salaried by the hospital (Bazzoli et al., 2000; Baker et al., 2014; Cuellar and Gertler, 2006).

2.1.2 How Hospital-Physicain Integration Can Affect Utilization

There are competing hypotheses for whether hospital-physician integration may decrease or increase utilization. One argument is that hospital-physician integration can decrease utilization by either increasing the efficiency of care delivery or providing incentives for hospitals and physicians to lower costs. Integration can increase efficiency by encouraging affiliated hospitals and physicians to develop systems to improve care coordination.[9] Robinson and Miller (2014) argue that improved care coordination can result in "less duplication of tests and treatments, substitution of

[9]For example, Burns and Muller (2008) find that integrated hospitals may be more likely to invest in programs where "a hospital and medical staff identify ... clinical practices that increase the hospital's operating costs without improving quality, to develop initiatives to eliminate such practices."

low-cost for high-cost settings where appropriate, and as a result, lower total expenditures." A related argument is that that integration could decrease the costly treatments by providing hospitals and physicians with a greater incentive to monitor costs and quality of care (Cuellar and Gertler, 2006; Madison, 2004).[10] Integration may also increase the use of payment systems (i.e., capitation or bundled payments) designed to lower costs and utilization.[11] Integrated hospitals in some cases (ISMs and MFs) even salary physicians which can curb physicians' financial incentives to provide excessive treatments compared to physicians who are reimbursed a set price for every service performed (Fee-For-Service).

Alternatively, hospital-physician integration could also increase the utilization of costly treatments by altering physicians' financial incentives. If hospitals financially acquire physician practices, Madison (2004) argues that such integration can increase the degree to which physicians internalize concerns about hospital profits. For example, if a hospital owns a physician practice (as in an ISM or MF), affiliated physicians have an increased incentive to perform treatments that increase hospital profits (Madison, 2004). Integration can also increase physicians' financial incentives to provide higher quality or a higher quantity of services through increased reimbursement prices. In some cases, previous evidence supports the conclusion that hospital-physician integration can increase affiliated hospitals' and physicians' market power, allowing them to charge higher reimbursement prices (Baker et al., 2014; Cuellar and Gertler, 2006; Neprash et al., 2015).[12] If integration increases hospital and physician reimbursement

[10]Cuellar and Gertler (2006) hypothesize that integration encourages investment in shared information systems between hospitals and physicians which facilitates monitoring costs and quality for affiliated hospitals and physicians. Madison (2004) further argues that hospital-physician integration makes each entity more dependent on the other's reputation. Therefore, integration can provide hospitals and physicians a greater incentive to monitor each other than non-affiliated hospitals and physicians.

[11]Cuellar and Gertler (2006) argue that integrated hospitals and physicians are better suited to overcome the internal principal-agent problems between hospitals and physicians to capitalize on the financial benefits from such payment systems.

[12]Baker et al. (2014) and Cuellar and Gertler (2006) find some evidence that hospital ownership of physician practices is associated with higher hospital prices in a nationwide sample of commercially insured patients and a combined sample of hospital discharges from Arizona, Florida and Wisconsin, respectively. Neprash et al. (2015) find hospital owned physician practices are associated increased health care spending but not associated with increased of utilization in a sample of Medicare patients. They interpret these findings as evidence of increased hospital prices. It is important to note that there is no evidence of a uniform effect of integration on hospital prices. In particular, these studies find no consistent evidence that contractual forms of hospital-physician integration

prices, it can provide an incentive to provide both a higher quantity of all treatments, and, potentially, higher cost treatments. Due to the competing theories as to whether hospital-physician integration can increase utilization, it is necessary to turn to data to answer this question empirically.

2.2 Empirical Strategy

2.2.1 Clinical Setting: Cesarean Sections in Childbirth

I study the effect of hospital-physician integration on utilization by looking at its effect on the use of Cesarean sections (C-sections) in childbirth. Childbirth represents a relevant clinical setting because it represents a binary decision between a high intensity, high cost treatment (C-sections) and a low intensity, low cost alternative (vaginal birth). C-sections are an intensive surgical procedure that utilize more resources during and after the procedure; C-sections require longer lengths of stay and have higher risks of complications (Johnson and Rehavi, 2016). Hospitals and physicians are generally reimbursed more for C-sections than vaginal births. The Truven Market Scan Study (2013) found that on average hospitals were reimbursed $27,866 for C-sections compared to $18,329 for vaginal births for commercially insured patients.

In many cases, the decision to perform a C-section can be subjective and clinical guidelines are not well defined (Johnson and Rehavi, 2016; Keirns, 2015). As a result, payers, for example, are not always able to accurately judge the medical necessity from diagnoses observed ex-post (Foo et al., 2017). Because of this information asymmetry between health care providers (hospitals and physicians) and patients and payers, providers typically have flexibility in deciding whether to perform C-sections (Foo et al., 2017; Johnson and Rehavi, 2016). There is a large body of evidence that C-sections rates respond to a variety of hospital and physician financial and legal incentives.[13]

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increase hospital prices. Ciliberto and Dranove (2006) also find no evidence that hospital-physician integration increases hospital prices in a sample of California hospitals from 1994-2001.

[13] Alexander (2016), Foo et al. (2017), and Gruber et al. (1999) document the effect of changes in hospital and physician reimbursement prices on the use of C-sections. Gruber and Owings (1996) find that C-section use responds to expected future shocks to physician income. Spetz et al. (2001) find that C-section use responds to physician financial and leisure incentives for patients in group

If hospital-physician integration affects utilization through altering physician incentives, C-sections are therefore a treatment that should respond to changes in hospital-physician integration. For example, if integration decreases unnecessary treatments through improving hospitals' ability to monitoring physician treatment decisions there should be a decrease in C-sections. While in some cases, C-sections are a life saving procedure, in others they are potentially unnecessary. The nation-wide C-section rate for the United States was 32.2% in 2014 despite the World Health Organization's finding that there is no benefit to a C-section rate above 15% (Hamilton et al., 2015; Gibbons et al., 2010).[14] Conversely, if integration encourages increases the use of treatments that increase hospital profits, integration should be associated with an increase in C-sections. C-sections are typically a very profitable treatment for hospitals, likely due to the fact that they have higher reimbursement prices than vaginal births and are the most common surgical procedure performed by hospitals.[15]

2.2.2 Data Sources

I use two primary data sources for my analysis. First, I use hospital discharge data from California's Office of Statewide Health Planning and Development (OSHPD) from 2005-2012. These data contain all discharges from California hospitals in my sample time period, and include patient diagnostic, demographic, insurance, and treatment information. This allows me to observe the treatments for patients giving birth (i.e., C-section vs. vaginal birth) and additionally control for a rich set of patient diagnostic and demographic characteristics.

Second, I supplement the OSHPD hospital discharge data with data from the American Hospital Association (AHA) Annual Survey. I match the OSHPD data to hospitals from the AHA survey by hand using the Medicare Provider numbers con-

model Health Maintenance Organizations (HMOs). Yang et al. (2009) find that malpractice lawsuit reform affects the use of vaginal births (versus C-sections) in births following previous C-sections.

[14]This prevalence of C-sections has not noticeably improved public health outcomes in the United States and is indicative of overuse: among Organsation for Economic Co-operation and Development (OECD) countries, the United States ranked 26$^{\text{th}}$ in infant mortality as of 2010 (CDC, 2014). Rosenberg (2016) quotes Jeffrey Ecker, the chairman of the American Congress of Obstetricians and Gynecologists' committee on obstetric practice: "[The rise of C-section rates] has not been paralleled by any important fall in rates of things like cerebral palsy."

[15]Johnson and Rehavi (2016) quote the Chief Obstetrician-Gynecologist for Sutter Health, a large hospital system in California: "Cesarean birth ends up being a profit center in hospitals."

tained in the AHA data. The AHA data include hospital characteristics and, importantly, indicator variables for whether hospitals report 6 forms of hospital-physician integrations: Independent Practice Association (IPA), Open Hospital Physician Organization (OPHO), Closed Hospital Physician Organization (CPHO), Management Service Organization (MSO), Integrated Salary Model (ISM), and Medical Foundation (MF).[16] I classify hospitals as reporting no physician affiliation if they report a value of 0 for each form of integration. Because these arrangements are not mutually exclusive, it is possible for hospitals to report multiple forms of integration.[17] As discussed previously, I group together OPHOs, CPHOs and MSOs as Physician Hospital Organizations (PHOs). Where other previous studies group together ISM and MF hospitals under the umbrella of Fully Integrated Organizations (Cuellar and Gertler, 2006; Baker et al., 2014), I leave these two forms as separate.[18]

2.2.3 Sample Description

I use observations where the patient is the mother and identify treatment and diagnoses using the Diagnosis Related Group (MS-DRG) codes and ICD-9 diagnostic and procedure codes. I make several notable sample restrictions. First, following the methodology of Kozhimannil et al. (2013), I limit my analysis to observations where patients are classified by the American College of Obstetricians and Gynecologists as low risk of receiving a C-section.[19] By restricting my sample to low risk pregnan-

[16]It is possible that some subset of physicians within the set of physicians who practice at a particular hospital are part of the hospital-physician arrangements reported in the AHA survey. I also cannot observe which physicians treat which patients. Consequently, I assume that Obstetrician/Gynecologists (OB/GYNs) participate in the form of hospital-physician integration reported.

[17]If a hospital reports multiple forms of hospital-physician arrangements, I cannot observe which arrangement OB/GYNS participate in. Consequently, I allow hospitals to be classified multiple forms of hospital-physician integration in my primary analysis. Baker et al. (2014) use a slightly different approach by classifying hospitals that report multiple forms of integration as only reporting the tightest form of integration. However, I later show that my results are robust to using their method of classifying hospitals with multiple forms of integration and to omitting these hospitals all together.

[18]The study most similar to mine, Madison (2004), finds that ISM hospitals are associated with increased treatment intensity for Medicare patients with Acute Myocardial Infarction (AMI). I leave ISMs separate from MFs because I am interested in observing whether ISMs, in particular, have a similar effect on the use of C-sections.

[19]Kozhimannil et al. (2013) define patients as low risk of receiving a C-section if they have not had a previous C-section and are full-term, singleton pregnancies with vertex presentation. As in

cies, I excluding patients with ex-ante conditions identified by medical literature as necessitating a C-section. This allows me to focus my analysis on observations where providers have clinical flexibility in which treatment to perform. I limit my sample to privately insured patients. Following Kozhimannil et al. (2013), I also exclude hospitals that perform fewer than 100 births in a calendar year. I omit patients outside of the 1^{st} and 99^{th} percentile of age observations, leaving me with a sample of mothers aged 16-42. I exclude patient observations with missing demographic, diagnostic, insurance or treatment information, and hospital observations that are not matched with information on their hospital-physician arrangements. One last notable sample restriction is the omission of Kaiser Permanente Hospitals. Kaiser Permanente Hospitals are vertically integrated between Kaiser Hospitals and the Permanente Medical Group (Witt et al., 2010). I identify the effect of hospital-physician integration from variation within hospitals over time; at Kaiser hospitals there will not be intertemporal variation in hospital-physician integration. The magnitudes of each sample restriction are reported in Table 2.2.

Table 2.3 reports descriptive statistics for my baseline sample. The C-section rate in this sample is substantially lower than the statewide or national average over this time period because I limit my analysis to low risk births. On average, there are more C-sections performed at integrated hospitals. It is interesting to note that across the types of integrated hospitals, though, C-section rates are relatively similar. Integrated hospitals are also larger and perform more births on average than non-integrated hospitals. One notable exception is that on average ISM hospitals actually perform the smallest number of annual births. Integrated hospitals also are typically located in more competitive hospital markets (with more hospitals) and more competitive insurer markets (lower concentration of HMOs - HMO HHI). This is consistent with the hypothesis that the trend towards hospital-physician integration is in response to the rise of managed care and the consolidation of managed care plans (Burns and Muller, 2008; Cuellar and Gertler, 2006; Gaynor, 2006).

Johnson (2017 a), I supplement this definition by also classifying low risk pregnancies as patients without diabetes and hypertension.

2.2.4 Estimation

I estimate the following linear probability model using Ordinary Least Squares (OLS) for the likelihood that patient j receives a C-section at hospital h in year t:

$$\text{C-section}_{jht} = \beta_0 + \beta_1 \text{Integration}_{ht} + \beta_2 X_{jht} + \beta_3 H_{ht} + \alpha_h + \alpha_t + \varepsilon_{jht} \qquad (2.2.1)$$

C-section$_{jht}$ is an indicator for whether the patient j received a C-section at hospital h in year t. X_{jht} is a vector of patient characteristics containing a patient's demographic, diagnostic, and insurance characteristics.[20] To account for some time varying hospital characteristics, H_{ht} controls for the total number of beds reported by each hospital, the natural logarithm of total birth discharges at each hospital in each year, and a hospital time trend following Ciliberto and Dranove (2006). H_{ht} also includes characteristics of each hospital's market, which I define as a Hospital Referral Region (HRR) using the Dartmouth Atlas: the number of hospitals in each HRR and the Herfindahl-Hirschman Index (HHI) of commercial Health Maintenance Organization (HMO) insurers.[21] I also include hospital and year fixed effects.

I estimate two primary specifications. First, I estimate a specification where Integration$_{ht}$ is an indicator for whether a hospital reports any form of hospital-physician integration. Second, I also estimate a specification where Integration$_{ht}$ is a vector of indicators for each form of integration : IPA, PHO, ISM, and MF. This specification allows the effect of integration vary across the forms of integration. By exploiting heterogeneity in the forms of hospital-physician integration, I can see which aspects of integration are associated with changes in C-section use. Table 2.1 summarizes how the various forms of integration may have different effects on

[20] A patient's race is classified as one of the following: Asian, Black, Native American/Eskimo/Aleut, or Other (with White being the excluded category). A patient's ethnicity is an indicator for whether she is Hispanic. The diagnostic characteristics I control for are labor complications mentioned by previous literature as predictive of C-sections (Currie and MacLeod, 2016; Foo et al., 2017; Gruber et al., 1999; Gruber and Owings, 1996; Kozhimannil et al., 2013; Srinivas et al., 2010; Spetz et al., 2001): cord prolapse, dystocia, fetal distress, herpes, maternal distress, and previa. I include an indicator for whether patients have insurance through a Health Maintenance Organization (HMO), other Managed Care Organization (MCO), or traditional Fee-For-Service (FFS) plan.

[21] I calculate the HHI of HMO plans following Johnson (2017 a). This measure calculates the sum of squared HMO shares of total hospital discharges in a HRR in each year. For a more complete discussion of this measure, see Appendix A.2.3.

C-sections use through the potential mechanisms described earlier. For example, if integration decreases the use of C-sections through better care coordination, there should be a negative effect on C-section use at PHOs, ISMs, and MFs.[22] Conversely, if hospital ownership of physician practices incentivizes physicians to perform more profitable treatments, ISMs and MFs should be associated with increased C-section use.

In Table 2.1, I make no predictions about whether hospital-physician integration can decrease C-sections through the use of payment systems designed to decrease utilization or increase C-sections due to higher reimbursement prices. I account for these mechanisms using control variables. For a more complete discussion, see Section 2.4.1.

2.2.5 Identification

The effect of hospital-physician integration on patients' likelihood of receiving a C-section is identified by variation in integration within hospitals over time. Table 2.4 illustrates the intertemporal variation in hospital-physician integration. Most of the variation in integration forms comes from hospitals switching from having no physician affiliations to a particular form of integration. Most forms of hospital-physician integration are persistent; once hospitals switch to a particular form they tend to stay in that form. Compared to the other forms of integration, a smaller number of hospitals switch in to an out of participating in an ISM. The lack of intertemporal variation in whether hospitals participate in ISMs creates a potential concern that a small number of ISM hospitals are driving the association between a hospital being part of an ISM and C-section use that I observe.

The primary concern with my analysis is that hospitals' decisions to integrate with physicians are not random. Unobservable hospital characteristics could be correlated with both hospital-physician integration and the decision to perform a C-section. For example, a hospital with unobserved preferences for cutting costs may be more likely to integrate with physicians and also less likely to perform C-sections. To account for

[22] Because IPAs primarily exist only to facilitate managed care contracting for affiliated hospitals and physicians, it is not clear that they are able to increase the coordination of care (Cuellar and Gertler, 2006).

time-invariant unobservable hospital characteristics, I include hospital fixed effects. I cannot, however, account for time-varying unobservable characteristics. Similar to previous studies (namely, Baker et al., 2014; Ciliberto, 2006; Madison, 2004; Koch et al., 2017), I assume that changes in unobservable hospital, patient, and physician characteristics correlated with hospital-physician integration are uncorrelated with my outcome variable of interest: a patient's likelihood of receiving a C-section.

I account for two particular concerns with my identification assumption. First, several previous studies hypothesize and find that hospital-physician integration can increase the reimbursement prices that hospitals charge insurers (Baker et al., 2014; Cuellar and Gertler, 2006; Neprash et al., 2015). If hospitals get bigger relative to the market by absorbing physician practices, then they have more leverage when negotiating with private insurers and can therefore charge higher reimbursement prices. It is possible that the difference between the reimbursement prices for C-sections and vaginal births is positively correlated with hospital reimbursement prices.[23] Consequently, if integration can increase reimbursement prices over time, integration may also increase the financial incentive for the integrated hospitals and physicians to perform C-sections over time. Changes in unobserved reimbursement prices, therefore, may positively bias the effect of hospital-physician integration that I observe. While I do not observe reimbursement prices directly, I control for measures of both hospital and insurer bargaining power that are likely to be correlated with reimbursement prices. I include the number of hospitals in each HRR and the concentration of HMOs in each HRR.

A second concern is that changes in hospital-physician integration could alter where patients deliver.[24] Koch et al. (2017) provide evidence that integration alters

[23]It is widely documented that C-sections have higher reimbursement prices (for both hospitals and physicians) than vaginal births. Consider the effect of an hospital bargaining power increases the reimbursement prices for all treatments. If all reimbursement prices are increased by the same proportion, the increase to the reimbursement price of C-sections will be larger in absolute terms than for the price of vaginal births. Therefore, the increase in reimbursement prices would result in a larger absolute difference in the reimbursement prices for C-sections and vaginal births. For a more complete discussion of this argument see Appendix B.1.

[24]Altering physician referral patterns is a hypothesized motivation behind hospitals acquiring physicians practices. Kocher and Sahni (2011) note that "hospitals are willing to take a loss employing [primary care physicians] in order to influence the flow of referrals to specialists who use their facilities."

physician referral patterns.[25] This could be problematic, for example, if hospital-physician integration causes physicians to steer patients who are likely to receive C-sections to hospitals where they have affiliations. To account for this concern, I measure the number of annual discharges to control for an increase in discharges at each hospital and also control for patient diagnostic characteristics predictive of C-sections.[26]

2.3 Results

Table 2.5 reports the effect of a hospital-physician integration on a patient's likelihood of receiving a C-section. As seen in column 1, C-sections are 2% (0.3 percentage points - pp) less likely in hospitals reporting any form of hospital-physician integration than in hospitals without physician affiliations. This effect is statistically significant at the one-percent level. The magnitude of this effect is similar to previous estimates of the effect of a $100 change physician compensation for C-sections.[27]

To see if particular forms of hospital-physician integration are driving the negative effect of hospital-physician integration on C-sections, I allow the effect of integration to vary by the form of integration. As seen in column 2 of Table 2.5, there is a statistically significant negative effect of integration on C-section use at PHOs and ISMs. C-sections are 7.3% (1.2 pp) less likely at integrated hospitals that are either part of a PHO and 6.9% (0.9 pp) less likely at integrated hospitals that are part of an ISM. It is interesting to note that the effects of a integration on C-section use at PHOs and ISMs are not statistically different, despite that fact that PHOs are a contractual form of integration and where ISMs are an ownership form of integration.

There is also a small negative relationship between a hospital-physician integration on C-section use at IPAs, although it is not statistically significant. While the

[25] Among other results, Koch et al. (2017) find that hospital acquisition of physician practices is associated with acquired physicians increasing the amount in hospital-based care they provide at the acquiring hospitals, and a decrease in the care the acquired physicians provide at other hospitals.

[26] Ideally, I would be able to account for which physicians treat patients. However, I do not observe physician information.

[27] Gruber et al. (1999) find that a $100 change in the difference between physician reimbursement prices for C-sections and vaginal births would be associated with a 3.9% change in C-section rates in a sample of Medicaid patients. In their sample, the average price difference between C-sections and vaginal births was $127.

other forms of integration are associated with decreased C-section use, there is a small positive relationship between integration and C-section use at MFs. However, depending on the specification, I cannot reject that this effect is statistically different from zero. For example, when I allow the effect of integration on C-section use to vary by the type of PHO (Table 2.5, column 3), the effect of integration on C-section use at MFs is significant at the 5% level.

The negative effect of hospital-physician integration on C-section use, in particular at PHOs and ISMs, is robust varying the way I classify forms of hospital-physician integration. Column 3 of Table 2.5 allows the effect of integration on C-section use to vary by type of PHOs (i.e., open PHO, closed PHO, MSO). All types of PHOs are associated with a significant reduction in C-section use relative to hospitals with no physician affiliations. It is interesting to note that the effects of OPHOs and CPHOs on C-section use are not statistically different. The effect of MSOs on C-section use is statistically significantly smaller in magnitude than the effect of OPHOs on C-section use.

One further concern could be that the negative effect of integration on C-section use at PHOs and ISMs and the null effects at IPAs and MFs could be biased by the way I classify hospitals that report multiple forms of hospital-physician integration. Column 5 of Table 2.6 presents the estimates from the baseline specification when I exclude hospitals that report multiple forms of hospital-physician integration. Column 6 of Table 2.6 presents the estimates the baseline specification when classify hospitals that report multiple forms of hospital-physician integration following Baker et al. (2014).[28] In both cases, the estimates of effect of integration on C-section use at IPAs, PHOs, ISMs, and MFs are consistent in sign and significance with the baseline specifications. The results are consistent when I relax my two primary sample restrictions by including Medicaid patients and by including patients who have a high risk of receiving a C-section.[29]

[28] Baker et al. (2014) classify hospitals that report multiple forms of integration as only reporting the tightest form. They classify forms of integration from tightest to loosest as follows: Fully Integrated Organizations (MF and ISM), MSO, CPHO, OPHO, IPA.

[29] Column 2 of Table 2.6 includes high risk patients. While the effects of each form of hospital-physician integration are consistent in sign and significance, it is interesting to note that the magnitudes of the coefficient estimates are also similar. Because C-section rates are higher when the sample includes high risk patients (0.32 compared to 0.14), this means that the magnitude of hospital-physician integrations effect on C-section use is smaller. This is not surprising as in this sample

2.4 Discussion: Why Does Hospital-Physician Integration Decrease C-sections?

To summarize, I find that hospital-physician integration decreases the use of C-sections. More specifically, C-sections are significantly less likely at PHOs and ISMs than at non-affiliated hospitals. This finding contrasts with Madison (2004), who finds that ISMs are associated with increased treatment intensity for Medicare patients with Acute Myocardial Infarction (AMI). The broader interpretation of both studies, though, is consistent: we find no evidence that contractual forms of integration (IPAs and PHOs) increase utilization and mixed evidence as to whether ownership forms (ISMs and MFs) of integration increase utilization. The finding that hospital-physician integration does not increase (and if anything decreases) utilization is consistent several previous studies (namely, Baker et al., 2014; Cuellar and Gertler, 2006; Neprash et al., 2015).

2.4.1 Potential Mechanisms

Using the results, it is possible to learn about how hospital-physician integration affects the use of C-sections, and by extension, utilization. To this end, I revisit the mechanisms described in the conceptual framework and compare the results to the predictions summarized in Table 2.1.

Improved Care Coordination; Improved Cost, Quality Monitoring: The results are consistent with the argument that hospital-physician integration decreases C-sections by improving care coordination, monitoring, or both. Namely, there seems to be little to no effect of IPAs on C-section use, and there is a significant, negative effect of PHOs and ISMs. Because these mechanisms are difficult to observe, though, I cannot definitely confirm that they are driving the results. One additional caveat with this narrative is that I do not find a similar, negative effect of hospital-physician integration on C-section use at MFs. Depending on the specification, I either observe

physicians likely have less clinical flexibility compared to the sample of only low risk births.

Column 3 includes Medicaid Health Maintenance Organization (HMO) patients and Column 4 additionally includes Medicaid Fee-For-Service (FFS) patients. The only notable discrepancy between these estimates and the baseline estimates is that the positive effect of MFs on C-section use is statistically significant when the sample includes Medicaid patients.

an effect that I cannot reject as statistically different from zero or a positive effect of integration on C-sections at MFs. However, it is possible that this result is indicative of a mechanism particular to MFs (that would not also affect ISMs) that has a larger, positive effect on C-section use. I revisit this discussion in Section 2.4.2.

Use of Payment Sytems Designed to Limit Utilization: To account for the possibility that hospital-physician integration decreases C-section use through alternative provider payment systems, I control for the percentage of each hospital's net revenue derived from capitation. I omit the capitation variable in my primary analysis because there are a substantial number of observations at hospitals that do not report this variable in the AHA survey data. Table 2.7 shows that the estimates from my baseline specification are not biased by omitting this control variable.[30] This finding is inconsistent with the hypothesis that hospital-physician integration decreases C-sections through the use of capitation payments.

Financial Ownership: If hospital ownership of physician practices affects C-section use by altering physicians' financial incentives, there should be a positive effect of integration on C-sections at hospitals with ownership forms of integration (ISMs and MFs). However, the results demonstrate a negative relationship between integration and C-section use at ISMs. The conclusion drawn by Madison (2004), for example, supports this mechanisms. However, it is possible that either result is particular to the different clinical settings (AMI vs. childbirth) or patient populations (Medicare vs. privately insured).

It is possible that the positive effect of integration on C-section use at MFs does lend some support to the argument that integration can increase utilization through the financial ownership mechanism. This finding would be consistent with Koch et al. (2017) and Madison (2004). However, depending on the specification, in some cases I cannot reject the effect of integration on C-section use at MFs as statistically different than zero. It is also difficult to reconcile this hypothesis with the negative effect of integration on C-section use at ISMs. My interpretation of these conflicting results, is that rather than providing support for the financial ownership mechanism,

[30]Column 6 estimates the baseline specification on the sample of all observations at hospitals that are matched with data on the capitation variable. Column 7 adds this variable to the baseline specification. The similar coefficient estimates in columns 6 and 7 implying that omitting the captiation variable does not bias my baseline results.

the positive effect of integration on C-section use at MFs is evidence of a mechanism particular to MFs.

Salaried Physicians: The results do not support the conclusion that integration decreases C-sections by employing salaried physicians. If this were the case, I should observe a negative effect of integration on C-section use at both forms of integrated hospitals that employ salaried physicians (ISMs and MFs). It should also be the case that the negative effect of ISMs and MFs are greater in magnitude than the effect of IPAs or PHOs, as neither of these integration form salary physicians. I find no evidence that MFs have a similar negative effect on C-section use as ISMs. I also find no evidence that there is any statistical difference in the effect of PHOs and ISMs on C-section use. Both points contradict the hypothesis that hospital-physician integration reduces C-section through the use of salaried physicians.

Higher Reimbursement Prices: My baseline specification attempts to account for this mechanism affecting my analysis by controlling for measures of hospital and insurer bargaining power plausibly correlated with reimbursement prices. However, I can see if my results are biased by omitting these measures. If, for example, I saw a smaller effect of integration on C-section use when I omit the bargaining power measures, it would provide some evidence that changes in reimbursement prices affect the use of C-sections. Table 2.7 shows that the estimates of the effect of integration on C-section use are not quantitatively different when I include and when I omit the bargaining power measures.[31]

Of the various mechanisms through which hospital-physician integration could decrease C-sections, the the results are primarily consistent with the hypothesis that integrated hospitals are better able to coordinate care, monitor hospital costs and quality of care, or both. This finding is consistent with the conceptual argument of Cuellar and Gertler (2006) that PHOs and ISMs should be better able to coordinate and monitor patient care than hospitals without physician affiliations and IPAs. To my knowledge, though, no previous studies document a similar negative effect of hospital-physician integration on utilization.

[31] Column 1 includes the baseline specification. Column 2 omits the bargaining power measures (hospital market characteristics).

2.4.2 Medical Foundations and Increased C-section Use

One remaining result that is not consistent with the care coordination or monitoring hypothesis is the positive association between MFs on C-section use. In this context, it is useful to understand the characteristics of MFs that are distinct from the other forms of integration (particularly, ISMs). MFs are required to be much larger than other forms of integration in California. For example, Witt et al. (2010) note that MFs are required to employ greater than 40 physicians across 10 specialties, and require greater than 27 full time physicians. and are required to be teaching hospitals (Witt et al., 2010). MFs are also required to be teaching hospitals (Witt et al., 2010). I address each of these characteristics in turn.

MFs may have very high start-up costs compared to other hospitals because of their size. One possibility is that integration causes an increase in the use of profitable procedures at MFs, more than other forms of integrated or non-integrated hospitals, to offset these start up costs. To test this possibility, in Table 2.7, I augment my baseline specification to include indicators for whether a MF is in its first year of operation and a time trend for how long a MF has operated. If MFs increased profitable procedures (C-sections), there should be a positive effect of an MF being in the first year of operation and a negative time trend. There is no indication there is an increase in C-sections at MFs in the first year of operation, contradicting that hypothesis. If the positive effect of integration on C-section use at MFs I observe is driven by MFs increasing the use of profitable procedures in their early years of operation, I should observe a a negative or at least a smaller positive effect of integration on C-section use at MFs in this specification. The results support the opposite conclusion.

Another possibility is that because I omit data on hospitals' teaching status, the effect of integration on C-section use at MFs could be incorporating the effect of a patient delivering at a teaching hospital.[32] For example, Kozhimannil et al. (2013) find that teaching hospitals have higher C-section rates than non-teaching hospitals on average. However, as shown in Table 2.7, my results are robust to controlling for hospitals' teaching status which implies that teaching status is not driving the positive

[32] I omit teaching status in the baseline specification because I there are a substantial number of observations in my baseline sample at hospitals that do not report their teaching status in the AHA survey data.

effect of integration on C-section use at MFs. Column 4 of Table 2.7 estimates the baseline specification on the sample of observations at hospitals matched with data on their teaching status. Column 5 additionally includes controls for hospital teaching status.[33] The estimates reported in columns 4 and 5 are not qualitatively or quantitatively different, implying that by baseline results are not biased by omitting the control variables for hospitals' teaching status.

It is difficult to compare these findings to previous studies because MFs are typically grouped together with ISMs (Baker et al., 2004; Cuellar and Gertler, 2006; Koch et al., 2017; Neprash et al., 2015; Robinson and Miller, 2014) or omitted from the analysis (Ciliberto and Dranove, 2006; Madison, 2004). Consequently, I am left to conclude that there is some unobservable characteristic of MFs or physicians which select into employment at MFs that is driving this effect.

2.5 Conclusion

I study the effect of hospital-physician integration on the use of C-sections in childbirth. In a sample of privately insured patients, I find that hospital-physician integration is associated with reduced C-section use compared to hospitals without physician affiliation. In particular, PHOs and ISMs are associated with decreased C-section use. Interestingly, this effect is persistent across forms of integration that rely on both contractual and ownership relationships between hospitals and physicians. These results are consistent with the hypothesis that hospital-physician integration reduces C-section use either through improving the coordination or monitoring of care, rather than by altering physician financial incentives.

I provide evidence that for some forms of integration - namely PHOs (open PHOs, closed PHOs, and MSOs) - hospital-physician integration can decrease utilization. More broadly, this study supports the conclusions drawn from previous studies that hospital-physician integration does not increase health care utilization, similar to Baker et al. (2014), Cuellar and Gertler (2006), and Neprash et al. (2015). Because I find that hospital-physician integration reduces C-sections in a sample of births that

[33]Specifically, using data from the AHA hospital survey, I include indicators for whether the hospital has a medical school affiliation or if the hospital is a member of the council of teaching hospitals.

are classified low risk of having a C-section, I find that integration reduces potentially unnecessary C-sections. This implies that integration can improve the quality of care, while reducing utilization.[34] It is important to note, though, that more work is necessary to determine whether my findings generalize to other treatment contexts or to other states.

The results presented in this chapter are generally consistent with previous evidence that looser forms of integration (contractual forms of integration: IPAs and PHOs) are not associated with the increases in hospital prices or increased health care spending. Combined, these findings support the argument that contractual forms of hospital-physician integration can help improve the efficiency of care delivery without eliciting anti-competitive concerns.

[34]Unnecessary C-sections can increase health care costs and also lead to worse health outcomes (Johnson and Rehavi, 2016).

2.6 Tables and Figures

Table 2.1: Predicted Effect of Hospital-Physician Integration on C-section use by Form of Integration

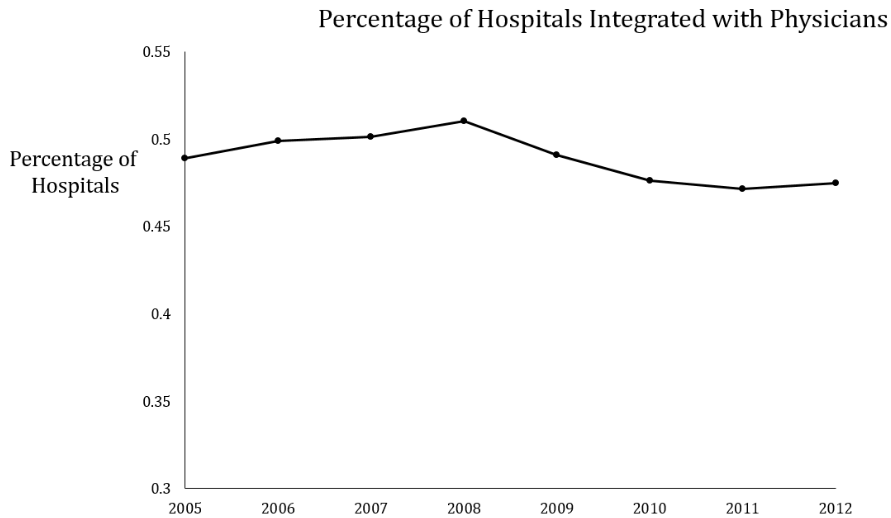
	Form of Integration:			
Mechanism:	IPA	PHO	ISM	MF
Improved Care Coordination		-	-	-
Increased Cost, Quality Monitoring		-	-	-
Salaried Physicians			-	-
Financial Ownership			+	+

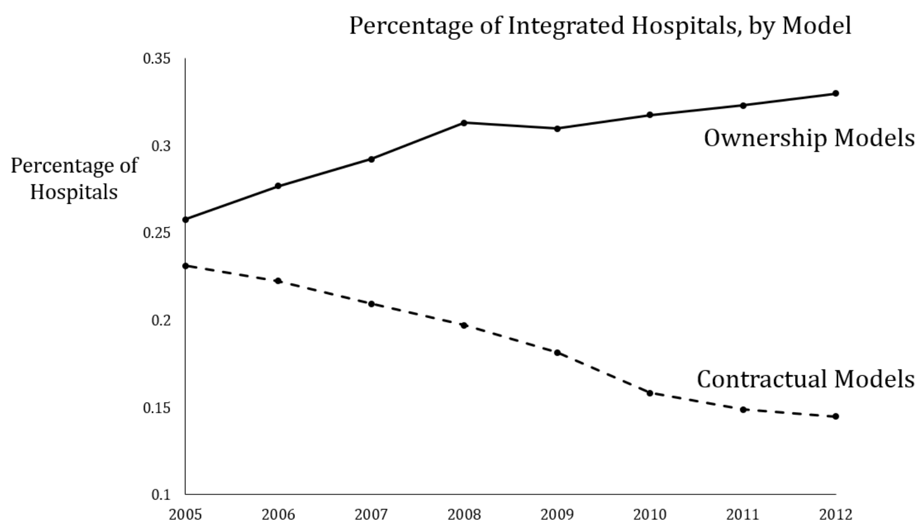
Table 2.2: Sample Restrictions

Sample:	Observations	C-section Rate
All Potential Observations	3542697	0.32
Excluding Kaiser Observations	3146967	0.32
Excluding High Risk Births	1989992	0.13
Excluding Medicaid Observations (Baseline Sample)	909668	0.14

Notes: All patient data is from the California OSHPD discharge data from 2005-2012. The baseline sample is defined as described in Table 2.3. Kaiser observations include all observations at Kaiser hospitals and patients with Kaiser Permanente insurance.

Figure 2.1: Hospital-Physician Integration, U.S. Hospitals 2005-2012





Notes: I classify hospitals as reporting forms of integration using the data contained in the American Hospital Association Annual Survey, 2005-2012. Ownership Models are defined as hospitals participating in an Integrated Salary Model or Medical Foundation hospitals. Contractual Models are defined as hospitals participating in an Independent Practice Association, Open or Closed Physician-Hospital Organization, or a Management Service Organization. Integrated hospitals are hospitals reporting any of the above forms of hospital physician arrangements.

Table 2.3: Descriptive Statistics by Form of Hospital-Physician Integration

			Contractual Forms		Ownership Forms	
Integration Form:	All	None	IPA	PHO	ISM	MF
C-Section	0.14	0.13	0.15	0.15	0.16	0.17
Patient Characteristics						
Age	29.9	29.7	30.2	30.2	30.6	30.8
Asian	0.16	0.18	0.15	0.12	0.14	0.15
Black	0.03	0.03	0.04	0.04	0.05	0.05
Native American	0.00	0.01	0.00	0.00	0.01	0.00
Other	0.13	0.13	0.13	0.13	0.14	0.09
White	0.67	0.66	0.68	0.70	0.67	0.71
Hispanic	0.28	0.28	0.27	0.27	0.22	0.23
Patient Insurance						
Private, HMO	0.50	0.51	0.49	0.46	0.49	0.43
Private, other MCO	0.44	0.43	0.43	0.47	0.39	0.50
Private, Traditional (FFS)	0.07	0.06	0.08	0.07	0.12	0.07
Hospital Characteristics						
Beds (total)	346.0	303.0	400.9	424.6	405.5	516.5
Num. of Birth Discharges	3166.3	2837.1	3801.5	3828.4	1936.2	4213.1
Hospital Market (HRR) Characteristics						
Number of Hospitals	27.0	20.7	35.6	32.8	37.7	37.9
HMO HHI	2147.3	2308.2	1904.6	1919.7	2247.1	1973.4
Observations	909668	454867	320794	146641	33868	148162

Notes: All patient data is from the California OSHPD discharge data from 2005-2012. Hospital-Physician arrangements are classified using AHA Annual Survey Data. Note: hospitals are able to report multiple hospital-physician arrangements. Some hospital characteristics (total number of beds) are also from the AHA Annual Survey Data. The baseline sample (All) includes privately insured patients between the ages of 16-42, observations at hospitals with more than 100 birth discharges in a calendar year. I additionally omit observations at Kaiser Permanente Hospitals. I exclude patients classified as high risk of receiving a C-section as defined by Kozhimannil et al. (2013) and Johnson (2017 a). I also exclude patients missing demographic, diagnostic or insurance information. I define a hospital's market as a Hospital Referral Region (HRR) according to the Dartmouth Atlas. Health Maintenance Organization (HMO) Herfindahl-Hircshman Index (HHI) measures the sum of commercial Knox Knee licensed plans (which I refer to as HMOs) shares of total HRR discharges in each calendar year, following Johnson (2017 a).

Table 2.4: Hospital-Physician Arrangement Transition Matrix

	Transition to:				
	None	IPA	PHO	ISM	MF
Transition from:					
None	693	36	18	6	18
Independent Practice Association (IPA)	37	190	4	0	11
Physician Hospital Association (PHO)	22	4	99	0	4
Integrated Salary Model (ISM)	6	1	0	83	1
Medical Foundation (MF)	13	5	2	0	100

Notes: This table reports changes in hospitals' form of hospital-physician integration over time in my baseline sample. Hospital-physician integration is classified using AHA Hospital Annual Survey Data. Note: hospitals are able to report multiple hospital-physician integration. For the purposes of illustrating changes in hospital-physician integration, in this table I treat hospitals that report multiple forms of integration as only reporting the tightest form, following Baker et al. (2014). Baker et al. (2014) the order forms of hospital-physician integration from tightest to loosest as follows: MF ISM, MSO, CPHO, OPHO, IPA.

Table 2.5: Effect of Hospital-Physician Integration on C-Section Use

Sample:	Low Risk	Low Risk	Low Risk
Dependent Variable:	C-Section	C-Section	C-Section
Variables:	(1)	(2)	(3)
Integrated Hospital	-0.003**	—	—
	(0.001)		
Contractual Forms:			
Independent Practice Association (IPA)		-0.000	-0.000
		(0.001)	(0.001)
Physician Hospital Organization (PHO)		-0.010***	—
		(0.002)	
Open PHO (OPHO)			-0.012***
			(0.002)
Closed PHO (CPHO)			-0.009*
			(0.005)
Management Service Organization (MSO)			-0.007***
			(0.002)
Ownership Forms:			
Integrated Salary Model (ISM)		-0.010**	-0.009**
		(0.004)	(0.004)
Medical Foundation (MF)		0.003	0.004**
		(0.002)	(0.002)
Patient Demographic, Diagnostic Characteristics	X	X	X
Hospital, Hospital Market Characteristics	X	X	X
Hospital, Year FE; Hospital Time Trend	X	X	X
Mean Dependent Variable	0.139	0.139	0.139
Number of Observations	909668	909668	909668
Adj. R^2	0.284	0.283	0.283

Notes: All patient data is from the California OSHPD discharge data from 2005-2012. Hospital-physician integration is classified using AHA Annual Survey Data. Note: hospitals are able to report multiple hospital-physician integration. Some hospital characteristics (total number of beds) are also from the AHA Annual Survey Data. The baseline sample is defined as described in Table 2.3. The integrated variable is defined as equal to 1 for any hospital reporting a form of integrated hospital-physician integration. Hospitals that report multiple hospital-physician integration are defined as having indicators equal to 1 for each form they report. The controls variables I include are as follows: Patient Demographic Characteristics - age, race/ethnicity (Asian, Black, Native American/Eskimo/Aleut, Other Non-White; Hispanic), indicators for whether the patient has HMO/other managed care or traditional (Fee-For-Service) insurance; Patient Diagnostic Controls - cord prolapse, dystocia, fetal/maternal distress, herpes, and previa; Hospital Characteristics - total number of beds, natural log(number of birth discharges); Hospital Market (defined as a Hospital Referral Region - HRR) Characteristics - number of hospitals in the HRR, HMO HHI. HMO HHI is defined as described in Table 2.3. Columns (3), (4) omit hospitals that reporting their hospital-physician arrangement as Medical Foundation hospitals. Standard errors are reported in parentheses; statistical significance denoted as follows: ** $p < 0.001$, ** $p < 0.05$, * p <0.10. All coefficients and standard errors are rounded to three digits to facilitate interpretation.

Table 2.6: Robustness Tests: Effect of Hospital-Physician Integration on C-Section Use

	Baseline		Including Medicaid		Varying Hybrid Classification	
Sample:	Low Risk	All	Low Risk	Low Risk	Low Risk	Low Risk
Hybrid Classification:	Cuellar & Gertler (2006)	Cuellar & Gertler (2006)	Cuellar & Gertler (2006)	Cuellar & Gertler (2006)	—	Baker et. al. (2014)
Dependent Variable:	C-Section	C-Section	C-Section	C-Section	C-Section	C-Section
Variables:	(1)	(2)	(3)	(4)	(5)	(6)
Independent Practice Association (IPA)	0.000	0.000	0.000	0.000	0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Physician Hospital Organization (PHO)	-0.010***	-0.008***	-0.009***	-0.008***	-0.013***	-0.011***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Integrated Salary Model (ISM)	-0.010**	-0.019***	-0.009***	-0.010***	-0.009*	-0.009**
	(0.004)	(0.004)	(0.003)	(0.002)	(0.005)	(0.004)
Medical Foundation (MF)	0.003	0.002	0.004**	0.006***	0.004	0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)
Include Medicaid HMO			X	X		
Include Medicaid FFS				X		
Include Hybrid Models	X	X	X	X		X
High Risk Characteristics		X				
Patient Demographic Diagnostic Characteristics	X	X	X	X	X	X
Hospital, Hospital Market Characteristics	X	X	X	X	X	X
Hospital, Year FE; Hospital Time Trend	X	X	X	X	X	X
Number of Observations	909668	1449530	1218921	1989992	749218	909668
Adj. R^2	0.284	0.519	0.289	0.315	0.271	0.284

Notes: All patient data is from the California OSHPD discharge data from 2005-2012. Hospital-physician integration are classified using AHA Annual Survey Data. Note: hospitals are able to report multiple hospital-physician integration. The baseline sample is defined as in Table 2.3. All control variables are as defined in Table 2.5. Column 2 includes births classified as being high risk of receiving a C-section according to Kozhimannil et al. (2013) and Johnson (2017 a). High risk characteristics include indicators for: full term, multiple gestation, previous C-section, malpresentation, obstructed labor, diabetes, and hypertension. Columns 3 and 4 include Medicaid HMO patients and column 4 includes Medicaid Fee-For-Service patients. In columns 1-4, hospitals that report multiple forms hospital-physician integration are defined as having indicators equal to 1 for each form of integration they report. Column 5 omits hospitals that report multiple forms of integration. Column 6 treats hospitals that report multiple forms of integration as only reporting the tightest form of integration following Baker et al. (2014), as described in Table 2.4. Standard errors are reported in parentheses; statistical significance denoted as follows: ** p < 0.001, ** p< 0.05, * p <0.10. All coefficients and standard errors are rounded to three digits to facilitate interpretation.

Table 2.7: Alternative Mechanisms

Sample:	Baseline	Baseline	Baseline	Matched with: Teaching Data		Capitation Data	
Dependent Variable:	C-Section	C-Section	C-Section	C-Section	C-Section	C-section	C-section
Variables:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
IPA	0.000	-0.001	0.000	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
PHO	-0.010***	-0.011***	-0.010***	-0.012***	-0.012***	-0.008***	-0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ISM	-0.010**	-0.011***	-0.010**	-0.013**	-0.013**	-0.014***	-0.014***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
MF	0.003	0.003	0.006**	0.008***	0.008***	0.006***	0.006***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Capitation Control							X
Teaching Controls					X		
MF 1st yr. control,Time Trend			X				
Hospital Market Characteristics	X		X	X	X	X	X
Patient Demographic, Diagnostic Characteristics	X	X	X	X	X	X	X
Hospital Characteristics	X	X	X	X	X	X	X
Hospital, Year FE; Hospital Time Trend	X	X	X	X	X	X	X
Mean Dependent Variable	0.138	0.138	0.138	0.145	0.145	0.142	0.142
Number of Observations	909668	909668	909668	691359	691359	720174	720174
Adj. R^2	0.284	0.284	0.284	0.281	0.281	0.300	0.300

Notes: All patient data is from the California OSHPD discharge data from 2005-2012. Hospital-physician integration are classified using AHA Annual Survey Data. Note: hospitals are able to report multiple hospital-physician arrangements. The baseline sample is defined as in Table 2.3. All control variables are as defined in Table 2.5. Compared to the baseline specification (column 1): column 2 omits Hospital Market characteristics; column 3 includes and indicator for whether MFs are in their first year of operation and a time trend for how many years each hospital has operated an MF; columns 4 and 5 estimates the baseline specification on a sample of only observations at hospitals that are matched with data on hospitals' teaching status; column 5 additionally includes an indicator for whether hospitals are affiliated with a medical school or a member of the council of teaching hospitals as reported in the AHA annual survey data; columns 6 and 7 restrict the sample to only observations at hospitals matched with data on the percentage of net revenue derived from capitation; column 7 additionally includes the capitation variable. Standard errors are reported in parentheses; statistical significance denoted as follows: ** p < 0.001, ** p< 0.05, * p <0.10. All coefficients and standard errors are rounded to three digits to facilitate

Chapter 3

Poorly Managed Care? The Effect of Medicaid Managed Care on Cesarean Section Use

Across the United States, Medicaid beneficiaries are receiving health care through managed care plans where previously they were covered through Fee-For-Service (FFS). The goal of moving Medicaid beneficiaries from FFS to Medicaid managed care (MMC) is to improve access to higher quality care and to lower costs (Duggan, 2004; Sparer, 2012). However, the shift from FFS to MMC represents a dramatic change in the provision of health care for Medicaid beneficiaries. In FFS Medicaid, the state reimburses a set price per-claim for all of their beneficiaries' medical claims to all providers who wish to participate. By contrast, in MMC, the state typically pays a managed care plan a fixed payment per beneficiary ('capitation' payment) to cover beneficiaries' medical claims (Duggan and Hayford, 2013). Because MMC plans receive a fixed amount of revenue per-beneficiary (the capitation payment), it has a financial incentive to limit their beneficiaries' health care utilization in order to limit their costs (beneficiaries' medical claims). The difference in supply incentives between FFS and MMC plans raises the question of whether shifting Medicaid beneficiaries from FFS to MMC impacts the care they receive.

I study whether switching from FFS to MMC plans affects utilization by altering which treatments Medicaid beneficiaries receive. The majority of the previous literature studying the effect of switching from FFS to MMC on utilization focuses on measures of whether patients use care. Previous evidence generally suggests that MMC can reduce various types provider visits (Bindman et al., 2005; Garrett and Zuckerman, 2005; Herring and Adams, 2011; Marton et al., 2014).[1] Several previous studies investigate the effect of switching from FFS to MMC on prenatal care use, however they reach different conclusions which are likely due to differences between their empirical settings (Aizer et al., 2007; Barham et al., 2013; Howell et al., 2004).[2] While the effect of MMC on whether patients use care is well studied, there is little evidence about whether the shift from FFS to MMC affects the type of care patients receive from providers. Kuziemko et al. (2017) provide evidence that relative to FFS, MMC plans can alter beneficiaries' quality of care.[3] I contribute to this literature by studying whether switching from FFS to MMC affects the specific treatments Medicaid beneficiaries receive.

I perform a case study of the effect of two California counties switching their administration of Medicaid from FFS to MMC on the use of Cesarean sections (C-sections) in childbirth. Childbirth is convenient treatment setting to study utilization because it typically presents providers with a binary choice between a high intensity, high cost procedure (C-section) and a low intensity, low cost alternative (vaginal birth). MMC plans have an incentive to limit the use of C-sections. I use hospital discharge data from California's Office of Statewide Health Planning and Development (OSHPD). While a few previous studies estimate the effect of switching from FFS to

[1]Bindman et al. (2005) find that MMC reduces hospitalizations. Garrett and Zuckerman (2005) find that MMC is associated with a reduction in emergency room use. Marton et al. (2014) find that MMC can reduce outpatient visits and professional service visits (physician, dental clinic, and public health clinic visits). In contrast to the other studies, Herring and Adams (2011) find that MMC can either decrease outpatient visits or can actually increase inpatient use depending on the type of MMC plan - whether the MMC is operated by a commercial insurer or a Medicaid-only plan, respectively.

[2]Aizer et al. (2007) find that MMC decreased the likelihood that patients used prenatal care in the first trimester in a sample from California, 1990-2000. Barham et al. (2013), conversely, find that MMC increased prenatal care use for a subset of the MMC population, the moderately disadvantaged, in a sample from California, 1991-2001. Howell et al. (2004) find MMC is associated with increased prenatal care use in a sample from Ohio, 1993-1998.

[3]Kuziemko et al. (2017) show that capitaiton payments from states to MMC plans provide plans an incentive to retain low cost beneficiaries. They provide evidence that MMC plans respond to this incentive by providing higher quality care to predictably low cost beneficiaries, and lower quality care to predictably high cost beneficiaries.

MMC on C-section, there is no consensus (namely, Aizer et al., 2007; Howell et al., 2004). Aizer et al. (2007), among other outcome measures, find no effect of switching from FFS to MMC on C-section use in a sample of California mothers from 1990-2000. Howell et al. (2004) find a reduction in repeat C-sections in MMC counties in a sample from Ohio.[4] Both of these studies, though, broadly focus on a number of outcome measures. I focus to the specific treatment decision of whether to perform C-sections in childbirth. In particular, I analyze a sample of patients for whom providers have greater clinical flexibility to choose between C-sections and vaginal births, and I account for a richer set of patient diagnostic characteristics. I additionally contribute by testing whether these previous findings on the effect of switching from FFS to MMC on C-section use generalize to different empirical settings: a set of different counties over a different time period (Aizer et al., 2007); and a different state (Howell et al., 2004; Koroukian et al., 2001).

I estimate the effect of switching from FFS to MMC on C-section use using a differences-in-differences design. I define the treatment group as all patients residing and delivering at hospitals in the switching counties, and the control group as all patients residing and delivering at hospitals in counties that maintain FFS for the duration of my time period. While most residents in switching counties are mandated to enroll in MMC, there are some exemptions allowing beneficiaries to maintain insurance through FFS. Because I assume that all beneficiaries in switching counties are mandated to enroll in MMC, I estimate an "intent-to-treat" effect. My primary identification assumption is that in the absence of switching from FFS to MMC, the treatment and control counties would have had similar trends in their C-section rates over time. I additionally assume that any patient movement between MMC and FFS counties is uncorrelated with their likelihood of receiving C-sections.

I find that switching from FFS to MMC was associated with a significant increase in C-section use. In particular, switching is associated with an 11.9% increase in C-sections. To support my primary identification assumption, I estimate a specification that allows the effect of being a beneficiary in a treatment county to vary by year. I

[4] Howell et al. (2004) note that their methodology improves upon a pair of previous studies (Oleske et al., 1998; Koroukian et al., 2001) that estimate whether C-sections are more likely in MMC or FFS counties. In particular, Howell et al. (2004) are better able to account for selection bias by studying the outcomes for patients who were and were not subject to mandated MMC before or after reform.

find that there is no evidence differential trends in C-section use between treatment and control counties prior to the treatment counties switching from FFS to MMC. Because I find that switching to MMC can increase the use of potentially unnecessary C-sections, my results are consistent with previous case studies finding that MMC, particularly in California, does little to improve the efficiency of care (Aizer et al., 2007; Barham et al., 2013) or decrease costs (Duggan, 2004; Duggan and Hayford, 2013; Sparer, 2012).

3.1 Background

3.1.1 Medicaid Managed Care in California

Beginning in the 1970s, California was the first state to offer Medicaid beneficiaries the option to receive care through Medicaid managed care plans (Tater et al., 2016). Initially, enrollment in MMC was voluntary and Medicaid beneficiaries primarily maintained insurance through FFS (Aizer et al., 2007). In order to try to try to limit the costs and improve the quality of providers that accepted Medicaid beneficiaries, California began mandating beneficiaries to enroll in managed care plans in certain counties (Barham et al., 2013). From 1983 to 2012, 30 of California's 58 counties switched their administration of Medicaid from FFS to MMC. The staggered timing of counties adopting mandated MMC enrollment provides a unique empirical context to study the effects of counties switching their administration of Medicaid from FFS to MMC.

In my sample time period (2006-2012), eight counties switched from FFS to MMC.[5] I specifically focus on two California counties (Merced and Sonoma counties) that began serving their beneficiaries through MMC plans in October of 2009 (CHCF, 2009). Prior to 2009, Medicaid beneficiaries in these counties were served through FFS. In October 2009, the counties shifted their Medicaid beneficiaries into a single, Medicaid-only HMO plan run by each county - referred to as County Organized Health System (COHS).[6] In California, for MMC counties enrollment in MMC

[5] San Luis Obispo switched from FFS to MMC in 2008. Merced and Sonoma counties switched in 2009. Kings, Madera, Marin, Mendocino, and Ventura counties switched in 2011.

[6] Medi-Cal is California's Medicaid agency. For notational simplicity, throughout the chapter

is mandatory; when Merced and Sonoma counties switched from FFS to MMC their beneficiaries were mandated to enroll in the COHS plan (Tater et al., 2016). The Merced and Sonoma switch in 2009 is the best empirical context within my sample time period because it is the only switch from FFS to MMC in my sample time period that occurs for multiple counties and allows me to observe multiple years before and after the switch.

3.1.2 Mechanisms: How Managed Care Can Affect Utilization

In practice, MMC - typically offered through a Health Maintenance Organization (HMO) - can limit utilization by influencing health care providers (hospitals and physicians) through several mechanisms.[7] Compared to FFS which allows beneficiaries to visit any provider that accepts Medicaid patients, Medicaid HMOs have a network of providers which their beneficiaries can visit. Similar to private HMOs, network inclusion can provide Medicaid HMOs with a tool to pressure health care providers to limit utilization through the implicit threat of excluding providers from their provider networks (Ma and McGuire, 2002). Working with a set network of providers may also allow Medicaid HMOs to limit utilization through facilitating better care coordination or review (Barham et al., 2013).

Medicaid HMOs could also affect utilization by altering the financial incentives facing providers. In particular, HMOs could capitate providers - that is, pay providers a fixed fee independent of the services provided (Aizer et al., 2007). Capitating providers could decrease utilization by shifting the financial burden of providing medical services to Medicaid beneficiaries (and the potential savings from avoiding services) from the HMO to providers - the agents who make treatment decisions.

I refer to Medi-Cal as Medicaid. COHS plans are operated by "local agencies created by [each county's] Board of Supervisors" (McCall et al., 2000). Sonoma county joined a COHS plan that is operated in conjunction with several other counties (Napa, Solano and Yolo counties). All of the counties that switched from FFS to MMC in my sample time period, except for Kings and Madera counties, offer MMC through COHS plans. In Kings and Madera counties enrollees are mandated to enroll in a plan operated by the county or a plan operated by a contracted commercial insurer.

[7]For the rest of the Chapter, I refer to Medicaid managed care plans as Medicaid HMOs. In my case study of two California counties switching their administration of Medicaid from FFS to MMC, both counties offer MMC through a Medicaid HMO.

Marton et al. (2014) find evidence that MMC plans that capitate providers are able to reduce utilization both compared to FFS and MMC plans that pay providers on a per-claims basis. Additionally, where FFS pays each participating provider the same reimbursement price, HMOs could negotiate with individual providers to pay different reimbursement prices. Some previous studies argue that Medicaid HMOs could lower reimbursement prices through the threat of network exclusion, however they find no consistent evidence that Medicaid HMOs are able to achieve such discounts (Sparer, 2012).[8] It is also possible, depending on the Medicaid FFS reimbursement prices in a particular state or market, that the reimbursement prices negotiated Medicaid HMOs could actually be higher than the Medicaid FFS reimbursement prices. In either case, it is possible that switching from Medicaid FFS to MMC could alter provider financial incentives (and therefore beneficiaries' utilization) through changing reimbursement prices.

3.1.3 Clinical Setting: Cesarean Section Use in Childbirth

I study the effect of switching from FFS to MMC on the use of Cesarean sections (C-sections) in childbirth. Childbirth is a relevant clinical setting because it presents providers with a binary decision between a high intensity, high cost treatment (C-section) and a comparatively low intensity, low cost alternative (vaginal birth). C-sections are an intensive surgical procedure that utilize more resources during and after the procedure; C-sections require longer lengths of stay and have higher risks of complications (Johnson and Rehavi, 2016). C-sections are generally more costly for insurers to reimburse than vaginal births. According to the Truven Market Scan Study (2013), on average hospitals were reimbursed $13,590 for C-sections compared to $9,131 for vaginal births for Medicaid patients.

While in some cases C-sections are a life saving procedure, in many cases the decision to perform a C-section can be subjective and clinical guidelines are not well defined (Johnson and Rehavi, 2016; Keirns, 2015).[9] In the cases where C-sections and

[8]In a review of the literature, Sparer (2012) summarizes that there is little evidence MMC achieves cost savings through lower reimbursement prices. One potential reason is that Medicaid "Fee-For-Service [reimbursement prices] are already so low that it is hard [for Medicaid HMOs] to get additional price discounts" (Sparer, 2012).

[9]In the United States, C-sections rates are so high that they suggest over-use. The nation-wide

vaginal births represent potentially substitutable treatments, Medicaid HMOs have an incentive to encourage providers to limit C-sections. Moreover, there is a large body of evidence that C-sections rates respond to changes in a variety of provider financial and legal incentives.[10] Childbirth is also a particularly relevant clinical setting for understanding the efficiency of Medicaid programs. Medicaid finances a significant portion of the population's maternal care, and, consequently, childbirth is a primary cost driver for Medicaid. For example, in 2011 50.4% of births in California - the state considered in this study - were financed by Medicaid (DHCS, 2011). Also, from 2003-2008, California's Medicaid agency spent more on pregnancy with delivery than any other treatment for FFS beneficiaries (CHCF, 2009).

3.2 Empirical Strategy

3.2.1 Data Sources and Sample Description

I use a differences-in-differences approach to estimate the effect of two California counties (Sonoma and Merced) switching their administration of Medicaid from FFS to MMC on the use of C-sections in childbirth for their beneficiaries. I use hospital discharge data from California's Office of Statewide Health Planning and Development (OSHPD) from 2006-2012. These data contain all discharges from California hospitals in my sample time period, and include patient diagnostic, demographic, insurance, and treatment information. This allows me to observe the treatments for patients giving birth (i.e., C-section vs. vaginal birth) and additionally control for a rich set

C-section rate for the United States was 32.2% in 2014 despite the World Health Organization's finding that there is no benefit to a C-section rate above 15% (Hamilton et al., 2015; Gibbons et al., 2010). This prevalence of C-sections has not noticeably improved public health outcomes in the United States. Among Organsation for Economic Co-operation and Development (OECD) countries, the United States ranked 26$^{\text{th}}$ in infant mortality as of 2010 (CDC, 2014). Rosenberg (2016) quotes Jeffrey Ecker, the chairman of the American Congress of Obstetricians and Gynecologists' committee on obstetric practice: "[The rise of C-section rates] has not been paralleled by any important fall in rates of things like cerebral palsy."

[10]Alexander (2016), Foo et al. (2017), and Gruber et al. (1999) document the effect of changes in hospital and physician reimbursement prices on the use of C-sections. Gruber and Owings (1996) find that C-section use responds to expected future shocks to physician income. Spetz et al. (2001) find that C-section use responds to physician financial and leisure incentives for patients in group model Health Maintenance Organizations (HMOs). Yang et al. (2009) find that malpractice lawsuit reform affects the use of vaginal births (versus C-sections) in births following previous C-sections.

of patient diagnostic and demographic characteristics. I use observations where the patient is the mother and I identify treatment and diagnoses using the Diagnosis Related Group (MS-DRG) codes and ICD-9 diagnostic and procedure codes.

Formally, I define patient observations as part of the treatment group if they are Medicaid beneficiaries that both reside and deliver at a hospital in one of the two counties that switch their administration of Medicaid from FFS to MMC (Merced and Sonoma counties). The majority of Medicaid beneficiaries in the treatment counties are mandated to enroll in the COHS plan. However, as noted by Aizer et al. (2007) and Barham et al. (2013), there were some exemptions to the mandate: undocumented pregnant women and pregnant women with income above the welfare threshold but below 200% of the federal poverty line were able to continue receiving coverage through FFS Medicaid. I cannot observe whether patients are undocumented immigrants or patient income in the OSHPD data; I cannot define whether patients are mandated to enroll in MMC in switching counties. I assume that all patients in the switching counties have insurance through the COHS plan after the switch from FFS to MMC. Using data on patients income, Barham et al. (2013) find that 77% of women residing in a COHS counties in their sample were subject to the mandate to enroll in the COHS plan. Because non-mandated beneficiaries may maintain FFS rather than opting to enroll in MMC, the effect of switching from FFS to MMC I observe is an "intent-to-treat" effect rather than the effect of treatment (switching from FFS to MMC) on the treated population (Medicaid beneficiaries that switch from FFS to MMC). Therefore, I may underestimate the effect of switching from FFS to MMC.

I define patient observations as part of the control group if they are Medicaid beneficiaries that both reside and deliver at a hospital in one of the counties that maintains Medicaid FFS throughout the duration of my sample time period.[11] By limiting my sample to patients who both live and receive treatment within the same county, I am eliminating the possibility that a Medicaid FFS patient could receive treatment in a MMC county (and vice-versa).

[11]These counties include: Humboldt, Imperial, Lake, Lassen, Mono, Nevada, Placer, San Benito, Shasta, Siskiyou, Sutter, Tehama, Toulomne, Yuba.

I restrict my sample to focus my analysis on observations where providers have clinical flexibility in which treatment to perform. Following the methodology of Kozhimannil et al. (2013), I limit my analysis to observations where patients are classified by the American College of Obstetricians and Gynecologists as low risk of receiving a C-section.[12] By restricting my sample to low risk pregnancies, I am excluding patients with ex-ante medical conditions identified by medical literature as necessitating a C-section. Compared to previous studies of the effect of switching from FFS to MMC on C-section use (namely, Aizer et al., 2007; Howell et al., 2004), this restriction allows me to focus on patients for whom C-sections and vaginal births are more likely to represent substitutable procedures. I also exclude hospitals that perform fewer than 100 births in a calendar year, following Kozhimannil et al. (2013). I omit patients outside of the 1st and 99th percentile of age observations, leaving me with a sample of patients aged 16-42. I exclude observations with missing demographic, diagnostic, insurance or treatment information.

Table 3.1 reports the descriptive statistics for my baseline sample. The C-section rate for my sample (10.0%) is substantially lower than the national average over this time period, even among Medicaid patients.[13] This difference is primarily due to restricting my sample to only include low risk births. Column 2 relaxes the sample restrictions on my baseline sample to include high risk births; the C-section rate in this sample is 28.9%. Comparing columns 3 and 4, C-sections are more prevalent in the control counties (11.6%) than they are in the treatment counties (7.7%). Figure 1 plots the C-section rates for the treatment and control counties over time. While the C-section rate is relatively stable over time in the control counties, there is a distinct increase in the C-section rate in the treatment counties. Interestingly, this increase in the C-section rate for the treatment counties coincides with the shift in the treatment counties from FFS to MMC (in 2009). This change in the treatment counties' C-section rate provides some suggestive evidence, counter-intuitively, that MMC may be associated with an increase in C-section rates.

[12]Kozhimannil et al. (2013) define patients as low risk of receiving a C-section if they have not had a previous C-section and are full-term, singleton pregnancies with vertex presentation. As in Johnson (2017 a), I supplement this definition by also classifying low risk pregnancies as patients without diabetes and hypertension.

[13]For example, in 2010, in a study of 33 states (including California) 32.8% of all births and 32.1% of Medicaid births received C-sections (Curtin et al., 2013).

The other notable discrepancy between the treatment and control counties is the difference in the nature of their hospital markets. On average, hospitals perform more births annually in treatment counties, and hospital markets are more competitive.[14] Control counties on average have fewer hospitals and are located more rural areas of the state.

3.2.2 Estimation

I estimate the "intent-to-treat" effect of counties switching from Medicaid FFS to MMC on the use of C-sections for their Medicaid beneficiaries. I estimate the following specification for whether patient j received a C-section at hospital h in year t:

$$\text{C-section}_{jht} = \beta_0 + \beta_1 \text{Treatment County}_h * \text{Post}_t + \beta_2 X_{jht} + \beta_3 H_{ht} + \alpha_h + \alpha_t + \varepsilon_{jht}$$

C-section_{jht} is an indicator for whether the patient j received a C-section at hospital h in year t. X_{jht} is a vector of patient characteristics containing a patient's demographic, diagnostic, and insurance characteristics.[15] To account for some time varying hospital and county characteristics, H_{ht} includes the following control variables: the natural logarithm of the number of birth discharges at each hospital, the number of hospitals in each county, the concentration of hospital birth discharges within each county, and the percentage of Medicaid birth discharges at each hospital.[16] I include for time-invariant hospital (and county) characteristics I include hospital fixed effects. I also

[14] I measure hospital competition using the Herfindahl-Hirschman Index of hospital birth discharges within counties ('hospital HHI'): the sum of squared hospital shares of county birth discharges. On average, the hospital HHI is lower for treatment counties than for control counties. This implies that the hospital market in the treatment counties is more competitive than in the control counties.

[15] A patient's race is classified as one of the following: Asian, Black, Native American/Eskimo/Aleut, or Other (with White being the excluded category). A patient's ethnicity is an indicator for whether she is Hispanic. The diagnostic characteristics I control for are labor complications mentioned by previous literature as predictive of C-sections (Currie and MacLeod, 2016; Foo et al., 2017; Gruber et al., 1999; Gruber and Owings, 1996; Kozhimannil et al., 2013; Srinivas et al., 2010; Spetz et al., 2001): cord prolapse, dystocia, fetal distress, herpes, maternal distress, and previa.

[16] I measure the concentration of hospital birth discharges using the Herfindahl-Hirschman Index (HHI): the sum of squared hospital shares of county birth discharges.

include year fixed effects. Following Aizer et al. (2007), I cluster observations at the county by year level.[17]

Treatment County$_h$ is an indicator for whether a patient both resides and delivers in a treatment county - one of the switching counties. Post$_t$ is an indicator for whether a patient delivers after the treatment counties switched from FFS to MMC. The coefficient of interest is β_1: the coefficient on the interaction of whether patients resides and delivers in a switching county after that county has switched from FFS to MMC. Because the two switching counties shifted from FFS to MMC in the middle of a calendar year (October, 2009), I estimate three specifications: 1) I define Post$_t = 1$ for all observations in 2009 and after; 2) I define Post$_t = 1$ for all observations after 2009; 3) I define Post$_t = 1$ for all observations after 2009 and omit all observations from 2009.

3.2.3 Identification

My estimate of the effect of counties switching from Medicaid FFS to MMC are identified by variation in the difference between treatment and control counties over time. My estimates rely on the following identifying assumption (parallel trends assumption): I assume that any time-varying unobservable characteristics correlated with counties switching from FFS to MMC are uncorrelated with patients' likelihood of receiving C-sections over time. In other words, I assume that the treatment and control counties would have had similar trending C-section rates if the treatment counties did not switch from FFS to MMC.

Figure 1 provides some visual support to this assumption. There are similar, slight-upward trends in the C-section rates for both treatment and control counties in the years prior to treatment, from 2006-2009. However, following 2009 (when the treatment counties switched from FFS to MMC), there is a sharp upward trend in the treatment counties' C-section rate that is not present for control counties. More formally, I test this assumption by performing an event study where I estimate the

[17]Ideally, I would cluster observations at the county level to allow for the possibility that errors may be correlated within counties over time. Unfortunately, there are only observations from 17 counties in my study. Clustering errors by county may therefore lead to a false rejection of the null hypothesis that my estimate for the effect of switching from FFS to MMC on C-section use is not statistically different than zero (Cameron and Miller, 2015).

effect of beneficiaries residing and delivering in a treatment county by year. This allows me to estimate whether there are differences in C-section rates between treatment and control counties in each year both before and after the treatment counties switched from FFS to MMC.

Another potential concern with estimating the effect of counties switching their administration of Medicaid from FFS to MMC is that patients with unobservable preferences for (or against) C-sections could voluntarily select into (or out of) FFS. This could happen through two channels. First, the results I observe would be biased if patients living in a MMC county could elect to receive Medicaid through FFS or MMC according to their preferences. For example, it is possible those not mandated to enroll in MMC may opt out of treatment (switching from FFS to MMC) by maintaining the FFS plan according to unobserved preferences for C-sections. However, I do not measure the effect of patients switching insurance from FFS or MMC. I rather estimate the effect of residing in a MMC versus FFS county. The effect of non-mandated beneficiaries opting to stay in FFS plans is only problematic to the extent that I may underestimate the effect of counties switching their Medicaid beneficiaries from FFS to MMC (because not all residents switched from FFS to MMC).

A second selection concern is that patients could move between FFS and MMC counties according to unobservable characteristics correlated with their likelihood of receiving a C-section (i.e., preferences for C-sections). Aizer et al. (2007) explicitly test for this possibility in their analysis. They provide evidence that their results are not biased due by the assumption that any patient movement between FFS and COHS plans is uncorrelated with their outcome variables of interest.[18] Consequently, I also assume that patient movement between treatment and control counties is uncorrelated with their unobserved characteristics correlated with their likelihood of receiving a C-section.

[18] Aizer et al. (2007) estimate the effect of mothers switching insurance from Medicaid FFS to MMC (specifically, into COHS plans) on various outcome measures (including C-section use) in a sample of California patients from 1990-2000. In particular, they estimate a specification where they define patients' county of residence as their first reported county of residence throughout the duration of the sample. Their results (in particular, the effect on C-section use) in this specification and their baseline specification are qualitatively and quantitatively similar.

3.3 Results: The Effect of Switching from FFS to MMC

Table 3.2 reports the effect of a county switching from FFS to MMC on the C-section use for its Medicaid beneficiaries. I find a positive association between a county switching from FFS to MMC and C-section use that is statistically significant at the 10% level. C-sections were 11.6% (1.2 percentage points - pp) more likely for Medicaid beneficiaries following the switch from FFS to MMC. Compared to previous literature, this effect is quite large. Gruber et al. (1999) find that a $100 increase in physician compensation for C-sections would be associated with 3.9% increase in C-sections for Medicaid patients.[19] However, this difference in magnitudes could be attributable to Gruber et al. (1999) including what I define as high risk patients in their sample.[20] For example, if I expand my sample to include high risk patients, I find that the effect of switching from FFS to MMC was smaller in magnitude (6.5% compared to 11.6%).[21]

The positive association between switching from FFS to MMC and C-section use is robust to varying how I specify the timing of the switch. One concern is that the treatment counties switched from FFS to MMC in the middle of the calendar year (in October of 2009). It is possible I may mistakenly classify observations as occurring

[19]Gruber et al. (1999) estimate the effect of the difference in the physician reimbursement prices between C-sections and vaginal births on the use of C-sections for Medicaid patients. The magnitude of their estimate implies that a $100 increase in the difference between the reimbursement prices for C-sections and vaginal births would be associated with a 3.9% increase in C-section use. For context, in their sample the average difference in the reimbursement prices for C-sections and vaginal births is $127.

[20]In particular, they include patients who have had previous C-sections and patients who do not have vertex presentation. For these patients, C-sections are medically more necessary (Kozhimannil et al., 2013). Physicians may have less clinical flexibility to perform vaginal births instead of C-sections for high risk patients. Consequently, by including these patients Gruber et al. (1999) may underestimate the effect of changes to changes in the relative reimbursement price for C-sections.

[21]I find that the positive effect of a county switching from Medicaid FFS to a Medicaid HMO on the likelihood of its medicaid residents receiving C-sections is robust to including high risk patients. Comparing columns 1-3 of Table 3.2 to columns 4-6, the effect of switching from FFS to Managed Care is consistent in both sign and significance for each specification. However, as seen in Panel B, the magnitude of the effect is smaller when including high risk patients. This supports the hypothesis that physicians have less flexibility to choose between performing a C-section or vaginal birth for high risk patients.

after the county had switched from FFS to MMC if I define the switch as occurring for all observations in 2009 or none of the observations in 2009. For example, consider an observation in January, 2009. If I classify all observations in 2009 as occurring after the switch from FFS to MMC, I would mistakenly classify this observation as occurring after the switch (which in reality occurred in October, 2009). Analogously, if I classify the switch as occurring for no observations in 2009, I would mistakenly classify observations from October to December, 2009 as occurring before the switch. The effect of counties switching from FFS to MMC, however, is consistent across specifications where I define the switch from FFS to MMC as having occurred for all observations in 2009 (column 1), no observations in 2009 (column 2), and omitting all observations from 2009 (column 3). The coefficient estimate is smallest for the specification where I define the switch from FFS to MMC as having occurred for all observations in 2009, which implies that by doing so I am underestimating the effect of switching from FFS to MMC. This is not surprising because the switch from FFS to MMC occurred late in the year (October, 2009). For this reason, from now on I refer to the specification defining treatment as occurring in 2010 as my preferred specification.

The primary empirical concern with my analysis is that the parallel trends assumption may be violated. To support this assumption, I perform an event study.[22] The results are presented in Table 3.3. I find no evidence differential trends between the control (FFS) and treatment (switching) counties in any of the years prior to the switch from FFS to MMC (2006-2009). I do find evidence that there are significantly more C-sections performed in the switching counties in the years following the switch from FFS to MMC. Moreover, the results of this event study are robust to including high risk patients (column 3), and to omitting observations from 2009 (columns 2 and 4). This provides evidence that my "intent-to-treat" estimate for the effect of counties switching from FFS to MMC on C-section use for their beneficiaries is not biased due to the parallel trends assumption.

[22]In this event study, I specify the switch from FFS to MMC as occurring in 2010, consistent with my preferred specification. Specifically, I estimate the effect of beneficiaries residing and delivering in a switching county by year. I omit the effect of residing and delivering in a switching county in the year that the switch occurs.

3.4 Discussion

3.4.1 Comparison to Previous Studies

I find that counties switching from FFS to MMC was associated with increased C-section use for their beneficiaries. The few previous studies on the effect of switching from FFS to MMC on C-section use reach different conclusions. The most similar study to my analysis, Aizer et al. (2007), finds no consistent evidence that switching from FFS to MMC affects C-section use. Their empirical context is similar: California counties switching their Medicaid beneficiaries from FFS to MMC operated through COHS plans. Our different results are most likely due to differences in our empirical designs. Aizer et al. (2007) primarily study the effect of mothers switching their insurance from FFS to MMC and use mother fixed effects to account for unobservable patient characteristics (specifically, patient preferences for or against C-sections). They also estimate estimate a specification with county fixed effects rather than mother fixed effects (similar to this study). In this specification, they estimate that switching from FFS to MMC in COHS counties was associated with a 1.9 pp increase in C-section use.[23] While their estimate is not statistically significant, it is remarkably similar in magnitude to the estimate presented in the previous section for the high risk population (2.1 pp).[24] The similarity of our coefficient estimates from specifications using county fixed effects suggests that the different conclusions drawn from our studies are primarily attributable to their inclusion of mother fixed effects in their primary specification.

Another potential explanation is that Aizer et al. (2007) and this study reach different conclusions due to focusing on different samples. I restrict my sample to a subset of patients where providers have more clinical flexibility to decide between C-sections and vaginal births. Aizer et al. (2007) do not exclude what I define as high risk births in their sample. I find evidence that switching from FFS to MMC is associated with a smaller impact on C-section use when I include high risk

[23]See Table 4, Panel A, Column 6 in Aizer et al. (2007).

[24]As discussed in the subsequent paragraph, Aizer et al. (2007) include what I define as high risk patients in their sample. Therefore, the most comparable estimates from my analysis would be the estimates where I include high risk patients in my sample: Table 3.2, columns 4-6.

patients in my sample. This finding is consistent with the hypothesis that providers have less flexibility to choose between performing a C-section or vaginal birth for these patients. Therefore, Medicaid HMOs have less ability to influence providers to substitute between the two treatment options for these patients. By including patients for whom C-sections and vaginal births do not represent substitutable treatments, Aizer et al. (2007) may underestimate the effect of switching from FFS to MMC on C-section use. One caveat to this potential explanation, though, is that when I include high risk patients (importantly, including those with previous C-sections), I still observe a significant, positive effect of switching from FFS to MMC on C-section use.

It is also possible that the different results presented in this and previous studies are due to differences in our empirical settings.[25] Compared to this study, Aizer et al. (2007) estimate the effect of switching from FFS to MMC on a sample of patients in different California counties in a different time period. Because MMC was operated by different Medicaid HMOs in the different counties considered in their analysis and in this study, there could be a heterogeneous effect of switching from FFS to MMC by county. The different conclusions in this study, Koroukian et al. (2001), and Howell et al. (2004) could also be driven by differences in how counties operate their MMC programs or differences between the two states' health care systems (California in this study; Ohio in Howell et al., 2004). It is important to note that Kourokian et al. (2001) estimate the difference in C-section rates between FFS and MMC patients rather than the effect of patients switching from FFS to MMC. The negative association between MMC and repeat C-section use they observe could also be explained by unobserved differences between FFS and MMC patients.[26]

The positive association between switching from FFS to MMC and C-sections (specifically in COHS counties) is broadly consistent with the conclusions from pre-

[25]I revisit this hypothesis later in the section.

[26]For example, Figure 1 shows that in my sample the C-section rates for FFS counties are consistently higher than the C-section rates for the switching counties - likely due to unobservable differences between counties. As a result, if I were to estimate the difference in C-section rates between FFS and MMC counties I would likely find that MMC is associated with lower C-section rates (consistent with their finding).

Both Aizer et al. (2007) and Howell et al. (2004), in contrast to Koroukian et al. (2001), are able to account for unobservable differences between FFS and MMC beneficiaries by using mother fixed effects.

vious case studies of California Medicaid. Aizer et al. (2007), while they find no effect on C-section use, do find that mothers switching from FFS to MMC experience a higher incidence of induction/stimulation of labor, and of fetal monitoring ("high-tech births") in COHS counties. Duggan (2004) also finds evidence that MMC is associated with increased government spending in COHS counties. To the extent that Duggan (2004) finds evidence that Medicaid beneficiaries in COHS counties were more expensive to cover, his finding is consistent with the results presented here that switching from FFS to MMC is associated with increased C-section use in COHS counties. The evidence in these previous studies supports the conclusion that MMC is associated with higher utilization and higher health care spending in COHS counties in California. However, the question of why MMC increases use and spending remains.

3.4.2 Mechanisms: Why Does MMC Increase C-sections?

The association between switching from FFS to MMC and increased C-section use is not consistent with the narrative that MMC is more effective at limiting utilization than FFS. One of the policy goals for switching from FFS to MMC was that by shifting the financial risk of paying medical claims to the contracted Medicaid HMOs, HMOs would have an incentive to limit utilization - either through selective contracting, better coordinated care, or by reforming provider payments. I provide evidence that Medicaid HMOs are not able to limit low risk C-sections for their beneficiaries. This implies that COHS plans are not able to limit costly treatments through such mechanisms. It is possible that the limitations of these utilization containment mechanisms are particular to COHS plans in California. For example, some evidence suggests that reforming provider payment systems (i.e., paying providers with capitation payments) can enable Medicaid HMOs to limit utilization (Marton et al., 2014). Hunt et al. (2001) found that COHS plans, though, typically reimbursed specialists (i.e., Obstetricians and Gynecologists - OB/GYNs - who generally decide whether to perform C-sections) for each medical claim. Further, the finding that switching from FFS to MMC increased C-section use is not consistent with COHS plans influencing utilization through paying providers (namely, OB/GYNs) on a capitated basis.[27]

One possible explanation for the increase in C-section use is that the shift from FFS to MMC changes provider (specifically, physician) financial incentives to perform C-sections. Specifically, switching from FFS to MMC could change the relative reimbursement prices for C-sections and vaginal birth.[28] In California, under FFS, all providers who accept Medicaid beneficiaries are paid for each service at the same rate across the state (Tater et al., 2016). Throughout my sample time period, the physician reimbursement prices for C-sections and vaginal births were effectively the same under FFS.[29] Under FFS, physicians have limited financial incentive to favor C-sections relative to vaginal births for Medicaid beneficiaries.

Conversely, in MMC reimbursement prices are determined through negotiations between the Medicaid HMOs and providers. In a 2001 survey of COHS plan reimbursement prices, Hunt et al. (2001) find that the majority of COHS plans set their reimbursement prices for specialists (i.e., OB/GYNs) as a percentage of the Medicare physician reimbursement price schedule. There is a persistent difference in the physician reimbursement prices for C-sections and vaginal births in the Medicare reimbursement price schedule.[30] If COHS plans that base their reimbursement prices

[27]If COHS plans paid providers on a capitated basis, the providers would get a fixed payment per patient and, in turn, be responsible for covering all of the patients medical services. Because C-sections are a more intensive procedure and typically necessitate more resources both during and after the procedure, capitated providers would therefore have an incentive to limit the number of C-sections they perform. If the COHS plans paid providers on a capitated basis, the switch from FFS to MMC should therefore result in a decrease in the C-section use.

[28]For the duration of this section, I specifically focus on the effect of switching from FFS to MMC on the reimbursements paid by Medicaid to physicians. It is possible (and, in fact, likely) that switching from FFS to MMC similarly affects the reimbursement prices paid on behalf of Medicaid beneficiaries to hospitals as well.

[29]As of 2009, the physician reimbursement price for obstetrical care (vaginal birth) was \$1390.14 compared to \$1390.97 for Cesarean delivery. In 2009 there was an update to California's Medicaid reimbursement price schedule. From 2001-2009, the physician reimbursement prices for obstetrical care (Current Procedure Terminology (CPT) code: 54900) and Cesarean delivery (CPT code: 59510) were \$1088.56 and \$1088.62, respectively. Data on California's Medicaid reimbursement price schedule are available online at: https://files.medi-cal.ca.gov/pubsdoco/rates/rateshome.asp.

[30]Medicare reimbursement prices vary across localities within California and over time. For example, in California in 2005 the difference between the physician reimbursements price for Cesarean delivery and obstetrical care ranged from \$218.87 to \$260.26; in 2012, the difference between the physician reimbursement prices ranged from \$221.37 to \$245.55. Historical data on the Medicare FFS physician reimbursement price schedule are available online at: https://www.cms.gov/apps/physician-fee-schedule/.

off of Medicare prices, there would be a difference between the reimbursement prices for C-sections and vaginal births. By increasing the difference in the reimbursement prices for C-sections and vaginal births, the shift from FFS to MMC would increase physicians' financial incentive to perform C-sections in COHS counties.[31] Numerous previous studies document the response of C-section rates to changes in physician reimbursement prices (namely, Foo et al., 2017; Gruber et al., 1999). Therefore, the difference in reimbursement prices could explain the association between switching from FFS to MMC and increased C-section use in COHS counties.

Ideally, to test this hypothesis I would be able to observe reimbursement prices. Unfortunately, because the reimbursement prices for the COHS plans are proprietary I cannot observe them directly. However, because the two switching counties provide MMC through two different HMOs, it is likely that they reimburse physicians through different price schedules. If the switch from FFS to MMC increased C-sections by changing physician reimbursement prices, there should be a heterogeneous effect of switching from FFS to MMC by county. For example, if the COHS plan in one of the counties was able to negotiate their reimbursement prices as a lower percentage of the Medicare reimbursement prices (compared to the COHS plan in the other county) the difference between the reimbursement prices for C-sections and vaginal births would also be proportionally smaller.[32] In this case, switching from FFS to MMC would increase providers' financial incentives to perform C-sections to a lesser degree; switching from FFS to MMC should have a smaller effect on C-section use in this county. If reimbursement prices are driving the effect of switching from FFS to MMC on C-section use, the effect of switching should therefore vary with the overall level of reimbursement prices negotiated by each COHS plan.

To test this hypothesis, I estimate a triple-difference specification where I allow the effect of switching from FFS to MMC to vary according to a measure correlated with reimbursement prices. Similar to the reimbursement prices negotiated between

[31]The shift from FFS to MMC would increase the reimbursement price difference conditional on two assumptions: 1) COHS plans set their negotiated reimbursement prices as a percentage of some base reimbursement prices (i.e., Medicare reimbursement prices) 2) there is a difference between the base reimbursement prices for C-sections and vaginal births. For a proof, and a more complete discussion of these assumptions and their validity see the Appendix B.1. For the duration of this section, I assume that the Medicaid HMOs in my analysis set their reimbursement prices as a percentage of the Medicare reimbursement prices; at the end of the section, I revisit this assumption.

[32]For a proof, see Appendix B.1.

commercial insurers and providers, the reimbursement prices negotiated by COHS plans presumably should be correlated with provider market power (Cooper et al., 2015).[33] If physicians within a particular county are more concentrated, the COHS plan would have fewer outside options to contract with and therefore the physicians can demand higher reimbursement prices. If physicians are more concentrated in a county, the COHS plan's reimbursement prices should be higher. This implies that the difference between the COHS plan reimbursement prices for C-sections and vaginal births should be greater in this county; switching from FFS to MMC would cause a bigger increase to physicians' financial incentives to perform C-sections in this county. I measure physician (OB/GYN) concentration using the Herfindahl-Hirschman Index (HHI) of hospital birth discharges within counties.[34] I estimate whether the effect of counties switching from FFS to MMC on C-section use varies with physician concentration (Hospital HHI_{ht}):[35]

$$\begin{aligned}
\text{C-section}_{jht} &= \beta_0 + \beta 1 \text{Treatment County}_h * \text{Post}_t * \text{Hospital HHI}_{ht} \\
&\quad + \beta_2 \text{Treatment County}_h * \text{Post}_t + \beta_3 \text{Treatment County}_h * \text{Hospital HHI}_{ht} \\
&\quad + \beta_4 \text{Post}_t * \text{Hospital HHI}_{ht} + \beta_5 X_{jht} + \beta_6 H_{ht} + \alpha_h + \alpha_t + \varepsilon_{jht}
\end{aligned}$$

Table 3.4 presents the estimates for this specification. The positive effect of counties switching from FFS to MMC on the likelihood that their beneficiaries receive C-sections is increasing in the level of physician concentration within counties. This relationship is statistically significant at the 5% level. Switching from FFS to MMC has a larger effect on C-section use in counties where negotiated reimbursement prices should be higher - and therefore where switching from FFS to MMC should cause

[33] Cooper et al. (2015) document a significant positive correlation between hospital concentration and hospital reimbursement prices.

[34] More formally, this measure is computed as the sum of squared hospital shares of county birth discharges. Ideally, I would measure physician concentration directly. Unfortunately, I do not observe physician identifiers in my data. I assume that physician concentration is correlated with the concentration of hospital birth discharges within counties. If physicians practice at multiple hospitals, it is possible that the concentration of hospital birth discharges will understate physician concentration.

[35] As mentioned in the discussion of my baseline results, I consider my preferred specification the specification defining treatment as occurring in 2010. I similarly define treatment as occurring in 2010 for this specification.

a bigger increase in physicians' financial incentives to perform C-sections.[36] The finding that the effect of switching from FFS to MMC on C-section use is correlated with reimbursement prices would be consistent with the conclusion that switching from FFS to MMC affects C-section use by changing providers' financial incentives to perform C-sections.

If the positive association between switching from FFS to MMC and C-section use is driven by a change in physician reimbursement prices, it could help explain the differences between this and previous studies. This conclusion suggests a heterogeneous effect of switching from FFS to MMC on C-section use across counties within states, and also across states, depending on how reimbursement prices are set. Such differences in the MMC settings between this study and the sample from Howell et al. (2004) could explain the differences in our results.

One caveat to the reimbursement price explanation is that it is possible that the COHS plans set their reimbursement price schedules according to the Medicaid FFS reimbursement prices (rather than Medicare prices). Under this scenario, the switch from Medicaid FFS to MMC would not cause a difference in the reimbursement prices for C-Sections and vaginal births.[37] If this were the case, MMC must increase the use of C-sections through some other channel. Further, the level of physician concentration would have to drive the effect of switching from FFS to MMC through a different mechanism. However, both the positive effect of switching from FFS to MMC and the evidence that this positive effect varies with the level of physician concentration in the switching counties are consistent with the reimbursement price explanation.

[36] One potential concern could be that this result is driven by changes in hospital HHI that is unrelated to the switch from FFS to MMC. To consider this possibility, I estimate whether hospital HHI had a different effect in control (FFS) counties before and after the treatment counties switched from FFS to MMC (Table 3.4, column 2). I find no evidence that this is the case.

[37] For a more complete discussion, see Section B.1 in the Appendix.

3.5 Conclusion

I estimate the "intent-to-treat" effect of two California counties switching from FFS to MMC on the use of C-sections in childbirth. I find that switching from FFS to MMC was associated with a 11.9% increase in the likelihood that beneficiaries received a C-section. This change is large in comparison to the previous literature that studies the effects of various health care provider financial and legal incentives on C-section use. The positive association between switching from FFS to MMC and C-section use provides three primary implications for the efficacy of MMC in COHS counties in California. First, I provide some evidence that shifting Medicaid beneficiaries from Medicaid FFS to MMC affects utilization by altering which treatments patients receive. In this context, I provide some evidence that MMC can affect treatment intensity, similar to Aizer et al. (2007). On the surface, this conclusion is inconsistent with previous findings that MMC reduced utilization as measured by hospitalization (Bindman et al., 2005) or decreased prenatal care use (Aizer et al., 2007). It is important to note, though, that I argue the switch from FFS to MMC increased C-sections due to a change in the reimbursement prices for the two relevant treatment options: C-section and vaginal births. It is therefore not clear that increased C-section use is indicative of an overall trend in utilization. For example, the change in C-section use may simply reflect a peculiarity of the Medicaid FFS reimbursement prices in California.

Second, even if the effect of counties switching from FFS to MMC on C-section use is not indicative of an overall utilization trend, I do provide evidence that switching to MMC alters patient treatment outcomes. Because I limit by analysis to patients who are classified as low risk of receiving a C-section by the American College of OB-GYNs, I show that switching from FFS to MMC increases potentially unnecessary C-sections. Unnecessary C-sections can both increase health care costs and also lead to worse outcomes (Johnson and Rehavi, 2016). Aizer et al. (2007) similarly find that switching from FFS to MMC is associated with reduced care quality in COHS counties.

Third, I provide some evidence that shifting beneficiaries from FFS to MMC may also be associated with increased costs in COHS counties. As discussed previously, C-sections are generally a more costly procedure than vaginal births. While more work is necessary to determine if the use of other costly treatments are also affected by switching from FFS to MMC, the use of C-sections in childbirth are an important Medicaid cost driver in their own right. For example, from 2003-2008 Medicaid FFS in California spent almost twice as much on covering pregnancies with delivery than any other condition (CHCF, 2009).[38] It is possible that Medicaid beneficiaries are on average more expensive for COHS plans to cover than beneficiaries in FFS counties are for the state to cover (because of the increased C-sections use). If the higher cost incurred by MMC plans in COHS counties is passed through from the COHS plans to the state (via the capitation payment) it is possible that switching from FFS to MMC could increase government spending in COHS counties. In this case, increased C-section use would be consistent with the finding from Duggan (2004) that MMC is associated with higher government spending, particularly in COHS counties.[39]

3.6 Limitations

There are several important limitations to the analysis presented in this chapter that necessitate caution when evaluating the implications of this study. First, this study is a case study of two counties switching their Medicaid beneficiaries to a single type of Medicaid-only HMO - a County Organized Health System - in one state. For example, it is possible that Medicaid HMOs operated by commercial insurers - rather than county operated HMOs - are more experienced and effective at limiting utilization or are better able to take advantage of economies of scale when negotiating reimbursement rates (Herring and Adams, 2011). Herring and Adams actually find that Medicaid-only HMOs are more likely to reduce utilization (inpatient stays and inpatient surgeries) compared to FFS than HMOs operated by commercial insurers. Aizer et al. (2007) find relatively consistent effects of patients switching from FFS to

[38]The total FFS spending on pregnancy with delivery was 5.9 billion compared to 3.2 billion for psychotic and schizophrenic disorders, the second most costly condition (CHCF, 2009).

[39]Duggan (2004), in a sample of Medicaid patients from California counties, finds that MMC is associated with increased government spending in COHS counties. He argues that this could be due to inflated capitation payments from the state to the COHS plans. One reason could be a lack of competition for the bids. If COHS counties face higher utilization from their beneficiaries than FFS counties - consistent with the increased use of C-sections - the increase in spending could alternatively be due to higher costs incurred by COHS counties.

MMC on utilization across California counties that only offer Medicaid only HMOs (COHS counties) and counties that also offer a commercially operated HMO.

Second, I focus on a subset of Medicaid HMOs (COHS plans) that do not appear to use capitation payments to providers for the particular subset of care delivery (childbirth) that I study. For example, Marton et al. (2014) find that a Medicaid HMO that pay providers via capitation payments are able to reduce the number of outpatient and professional visits relative to FFS where a Medicaid HMO that primarily reimburses providers on a claims basis does not. Future work could address this problem. I could expand the study to additionally consider the effect of switching from FFS to MMC in other California counties with different forms of MMC that include plans operated by commercial insurers. I could also expand the study to consider treatments that are likely to be affected by MMC plans capitating providers (namely, primary care).

Third, in this study I only evaluate the effect of switching from FFS to MMC on one particular treatment. Further work is necessary to extrapolate whether MMC has a similar effect on the use of other treatments that may be affected by switching from FFS to MMC. For example, it could be the case that other treatments exhibit decreased use under MMC. In this case, the results presented in this study would likely serve as an outlier because the switch from FFS to MMC resulted in an increase in C-sections due to a quirk in California's Medicaid FFS reimbursement price schedule for these two particular treatments (C-sections and vaginal births).

Fourth, because I cannot differentiate between residents that are and are not mandated to enroll in MMC plans it is possible that my results are biased by assuming that all residents that receive treatment in COHS counties following the switch from FFS to MMC have insurance through the COHS plan. Consequently, it is possible that my estimates represent a lower bound for the effect of switching from FFS to MMC in COHS counties.

Lastly, it is possible that my estimates are biased by the possibility that there is endogenous selection by Medicaid beneficiaries into or out of counties with MMC. However, a previous study by Aizer et al. (2007) in a sample of California patients found little evidence that this concern biased their results. However, the differences between the estimates of the effect of switching from FFS to MMC in COHS counties when using county fixed effects (this study; Aizer et al., 2007) and using mother fixed effects (Aizer et al., 2007) suggests that unobservable patient characteristics may be driving the results observed in the county fixed effects specifications. Future work is necessary to see if the results presented in this study would generalize to using mother fixed effects to better account for selection bias.

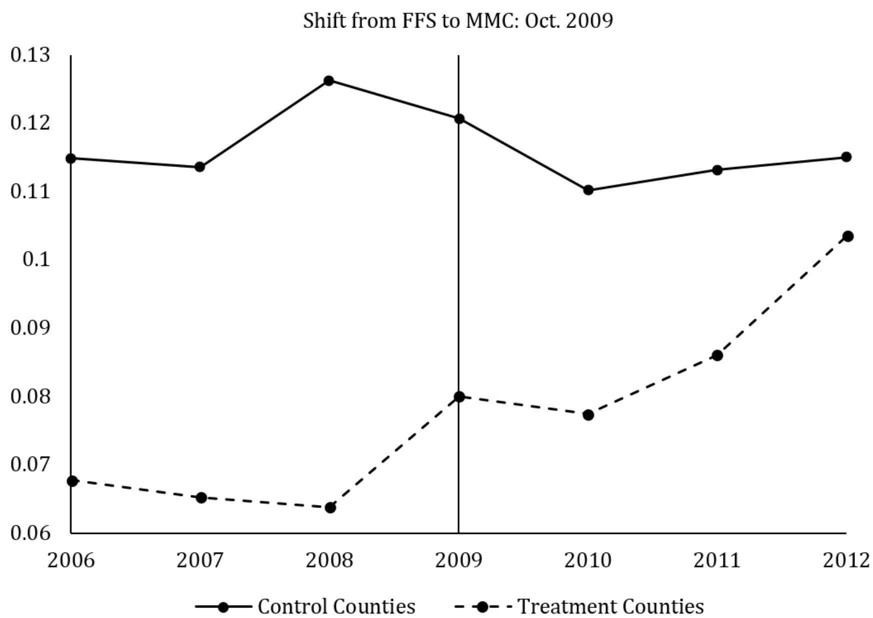
3.7 Tables and Figures

Table 3.1: Descriptive Statistics: Variable Means by County Type

Counties: Include High Risk Births?	All No	All Yes	Control No	Treatment No
C-Section	0.10	0.29	0.12	0.08
Patient Characteristics				
Age	24.6	25.4	24.4	25.0
Asian	0.04	0.04	0.02	0.06
Black	0.02	0.02	0.01	0.03
Native American/Eskimo/Aleut	0.01	0.02	0.02	0.01
Other	0.18	0.18	0.16	0.21
White	0.75	0.75	0.79	0.70
Hispanic	0.53	0.54	0.43	0.67
Hospital Characteristics				
Annual Birth Discharges, Hospital	1501.2	1494.6	1259.1	1825.3
HHI of Hospital Birth Discharges, County	6274.8	6237.9	7363.3	4817.1
Number of Hospitals in County	2.6	2.6	2.0	3.4
% of Hospital Birth Discharges from Medicaid	0.63	0.63	0.60	0.68
Observations	44477	70018	25464	19013

Notes: All patient data is from the California OSHPD discharge data from 2006-2012.The baseline sample (All) includes Medicaid patients who receive treatment in their county of residence, between the ages of 16-42, observations, at hospitals with more than 100 birth discharges in a calendar year. I exclude patients classified as high risk of receiving a C-section as defined by Kozhimannil et al. (2013) and Johnson (2017 a). I also exclude patients missing demographic, diagnostic or insurance information. The control group includes observations in all counties that deliver Medicaid through FFS throughout the duration of my sample: Humboldt, Imperial, Lake, Lassen, Mono, Nevada, Placer, San Benito, Shasta, Siskiyou, Sutter, Tehama, Tuolomne, Yuba. The treatment group includes observations in the counties that switch from Medicaid FFS to MMC in 2009: Merced, Sonoma.

Figure 3.1: C-section Rates in Control vs. Treatment Counties



Notes: This figure plots the percentage of patients in the baseline sample that received C-sections in the treatment and control counties in each year. All patient data is from the California OSHPD discharge data from 2006-2012. The baseline sample, treatment counties, and control counties are defined as in Table 3.1.

Table 3.2: Effect of Switching from FFS to MMC

Panel A: Regression Results						
Sample:	Low Risk			Including High Risk		
Post_t Value in 2009:	$\text{Post}_{2009} = 1$	$\text{Post}_{2009} = 0$	$\text{Post}_{2009} = -$	$\text{Post}_{2009} = 1$	$\text{Post}_{2009} = 0$	$\text{Post}_{2009} = -$
Dependent Variable:	C-section	C-section	C-section	C-section	C-section	C-section
Treatment County_h x Post_t	0.012**	0.012*	0.012*	0.019***	0.021***	0.021***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
High Risk Characteristics				X	X	X
Hospital Characteristics	X	X	X	X	X	X
Patient Characteristics	X	X	X	X	X	X
Hospital, Year FE	X	X	X	X	X	X
Observations	44477	44477	37796	70018	70018	59567
R^2	0.302	0.302	0.294	0.576	0.577	0.577
Panel B: The Effect of Switching from FFS to HMO on C-section use						
Effect of Switching (%)	11.6	11.9	12.5	6.5	7.3	7.4
Mean Dependent Variable	0.100	0.100	0.099	0.289	0.289	0.289

Notes: All patient data is from the California OSHPD discharge data from 2006-2012. The baseline sample, treatment counties, and control counties are defined as in Table 3.1. I define the Post_t variable as follows: in columns 1,2,4,5 I define $\text{Post}_t = 1$ for observations in 2009 and later; in columns 3 and 6 I define $\text{Post}_t = 1$ for observations in 2010 or later. In columns 1 and 4, I omit all observations from 2009. Columns 1-3 report the estimates from the baseline specification on the baseline sample, column 4-6 report additionally include births classified as high risk of receiving a C-section. The controls variables I include are as follows: Patient Demographic Characteristics - age, race/ethnicity (Asian, Black, Native American/Eskimo/Aleut, Other Non-White; Hispanic); Patient Diagnostic Controls - cord prolapse, dystocia, fetal/maternal distress, herpes, and previa; Hospital Characteristics - total number of beds, natural log(number of birth discharges), number of hospitals in hospital's county, the HHI (sum of squared hospital shares) of hospital birth discharges in each county in each year, and % of hospital's birth discharges from Medicaid. High risk characteristics include indicators for: full term, multiple gestation, previous C-section, malpresentation, obstructed labor, diabetes, and hypertension. Robust standard errors are clustered at the county by year level and are reported in parentheses; statistical significance denoted as follows: ** p < 0.001, ** p< 0.05, * p <0.10. All coefficients and standard errors are rounded to three digits to facilitate interpretation.

Table 3.3: Event Study: Effect of Treatment County by Year

Sample:	Low Risk		Including High Risk	
Include 2009?	Yes	No	Yes	No
Dependent Variable	C-section	C-section	C-section	C-section
Treatment County$_h$ x 2006	-0.001	-0.002	-0.002	-0.001
	(0.008)	(0.008)	(0.009)	(0.009)
Treatment County$_h$ x 2007	0.000	0.002	-0.007	-0.006
	(0.007)	(0.008)	(0.009)	(0.009)
Treatment County$_h$ x 2008	-0.003	-0.002	0.001	0.002
	(0.007)	(0.007)	(0.009)	(0.009)
Treatment County$_h$ x 2009	0.006		0.005	
	(0.010)		(0.009)	
Treatment County$_h$ x 2011	0.020**	0.019**	0.032***	0.031***
	(0.007)	(0.007)	(0.009)	(0.009)
Treatment County$_h$ x 2012	0.018	0.017	0.026**	0.026**
	(0.013)	(0.012)	(0.013)	(0.012)
High Risk Characteristics			X	X
Hospital Characteristics	X	X	X	X
Patient Characteristics	X	X	X	X
Hospital, Year FE	X	X	X	X
Observations	44477	37796	70018	59567
R^2	0.301	0.293	0.576	0.575

Notes: All patient data is from the California OSHPD discharge data from 2006-2012. The baseline sample, treatment counties, and control counties are defined as in Table 3.1. In each specification, I omit the variable for observations being in the treatment county in the year of treatment, which I define as 2010; all coefficients on the effect of being in the treatment county by year are therefore in comparison to being in the treatment county the treatment year, 2010. Columns 1 and 2 include the baseline sample. Columns 3 and 4 additionally includes births classified as high risk. Columns 2 and 4 omit all observations from 2009. The controls variables are defined as in Table 3.2. Robust standard errors are clustered at the county by year level and are reported in parentheses; statistical significance denoted as follows: ** p < 0.001, ** p< 0.05, * p <0.10. All coefficients and standard errors are rounded to three digits to facilitate interpretation.

Table 3.4: Does the Effect of Switching from FFS to MMC Vary by County?

Sample:	All Counties, Low Risk	Control Counties, Low Risk
Post_t Value in 2009:	$\text{Post}_{2009} = 0$	$\text{Post}_{2009} = 0$
Dependent Variable:	C-section	C-section
Treatment County_h x Post_t	0.069**	
x Hospital HHI, County_{ht}	(0.027)	
Post_t x Hospital HHI, County_{ht}	0.000	-0.004
	(0.019)	(0.019)
Pairwise Interactions	X	X
Hospital Characteristics	X	X
Patient Characteristics	X	X
Hospital, Year FE	X	X
Observations	44477	25456
R^2	0.301	0.306

Notes: All patient data is from the California OSHPD discharge data from 2006-2012. The baseline sample, treatment counties, and control counties are defined as in Table 3.1. Column 1 includes the baseline sample. Column 2 only includes observations from the control counties. Both columns 1 and 2 define $\text{Post}_t = 1$ for observations in 2010 or later. All variables are defined as in Table 3.2. Robust standard errors are clustered at the county by year level and are reported in parentheses; statistical significance denoted as follows: ** p < 0.001, ** p< 0.05, * p <0.10. All coefficients and standard errors are rounded to three digits to facilitate interpretation.

Appendix A

Appendix to Chapter 1

A.1 Mathematical Appendix

A.1.1 Insurer Cost Function

From Equation 1.2.3, insurer i's expected marginal cost is a function of each insurer's investment $\vec{x} = (x_1, ..., x_n)$:

$$\begin{aligned} c_i(\vec{x}) &= r_{VB}\hat{S}(\vec{x}) + r_{CS}[1 - \hat{S}(\vec{x})] \\ &= r_{VB}\left[\frac{t - d + x_i + \sum_{j \neq i} \gamma x_j}{2t}\right] + r_{CS}\left[\frac{t + d - x_i - \sum_{j \neq i} \gamma x_j}{2t}]\right] \\ &= \left[r_{CS} - (r_{CS} - r_{VB}) * \left(\frac{t-d}{2t}\right)\right] - \left[\frac{r_{CS} - r_{VB}}{2t}\right] x_i - \left[\gamma \left(\frac{r_{CS} - r_{VB}}{2t}\right)\right] \sum_{j \neq i} x_j \\ &= c_0 - c_1 x_i - c_2 \sum_{j \neq i} x_j \end{aligned} \tag{A.1.1}$$

Note: $\frac{\partial c_i}{\partial x_j} = c_2 = \gamma c_1 = \gamma \frac{\partial c_i}{\partial x_i}$.

Insurer i's cost function is:

$$C_i = c_i(x_1, ..., x_n) * q(p_1, ..., p_n) - V(x_i) \tag{A.1.2}$$

$q(p_1, ..., p_n)$: demand for insurer i as a function of premiums for all insurers.
$V(x_i) = \frac{\nu x_i^2}{2}$: the fixed cost of investment.

A.1.2 Insurer Demand Function

Following Vives (1999), I use the following linear demand function for insurer i as a function of the prices from all n insurers:

$$q_i(p_1, ..., p_n) = a_n - b_n * p_i + z_n * \sum_{j \neq i} p_j \tag{A.1.3}$$

$$a_n = \frac{\alpha}{\beta + (n-1)\delta} \qquad b_n = \frac{\beta + (n-2)\delta}{(\beta + (n-1)\delta)(\beta - \delta)} \qquad z_n = \frac{\delta}{(\beta + (n-1)\delta)(\beta - \delta)}$$

The above demand function is derived from the following quadratic utility function:

$$U(\vec{q}) \;=\; \alpha \sum_{i=1}^{n} q_i - \frac{1}{2}\left(\beta \sum_{i=1}^{n} q_i^2 + 2\delta \sum_{j \neq i} q_i q_j\right) \tag{A.1.4}$$

$\alpha > 0$, $\beta > 0$ characterize patients' expected utility from buying a single insurer's product (insurance plan). Intuitively, α can capture characteristics of a health plan that are constant upon buying insurance (i.e., customer service, a provider network) and β can capture characteristics of the health insurance plan that vary with the quantity of insurance (i.e., cost sharing parameters that may vary within insurer between plans of different qualities). $\delta \in (0, 1)$ represents the degree of product differentiation between any two insurers i's and j's, plans. For example, this could represent the quality of one insurer relative to another (i.e., the relative quality in provider networks). I assume insurers are symmetrically differentiated for simplicity. I also assume α and β is the same for all insurers for all patients. For simplicity, I am treating the insurers as identical in their reimbursement prices for C-sections and vaginal births, which are exogenous to the model. Additionally, consistent with the uniform distribution of patient systems, all patients' expected value of health insurance is the same. I assume that α is sufficiently large such that patients find it optimal to buy insurance. I assume that $\alpha > 0$ - a patient's marginal utility from purchasing a plan - is sufficiently large for patients to find it optimal to purchase positive quantities. Following Vives (1999), I assume $\beta > \delta > 0$. For simplicity, following Qiu (1997), I assume $\beta = 1$; this implies that $\delta \in (0, 1)$.

One important drawback of this approach is that this demand function is derived from a utility function where the consumer derives utilities from consuming quantities of each of the n products $(q_1, ..., q_n)$. This allows consumers to purchase positive quantities of each insurer's product. In the context of a consumers purchasing an insurance plan, this is problematic because in reality consumers typically do not purchase multiple insurance plans. However, it is important to remember that the goal of this theoretical exercise is to understand the effect of spillover and competition on insurers' optimal choice of investment. For a given number of firms, solving a model using a discrete choice demand model (i.e., Logit) ultimately yields qualitatively similar comparative statics for the effect of the number of insurers and competition on optimal insurer investment decisions. Therefore, for mathematical simplicity I proceed with my analysis using the linear demand function.

A.1.3 Optimal Insurer Premiums

Given the investment of all insurers $\vec{x} = (x_1, ..., x_n)$, insurer i chooses their premium to maximize profits given:

$$\max_{p_i} \quad [a_n - b_n * p_i + z_n * \sum_{j \neq i} p_j] * [p_i - c_i(\vec{x})] - V(x_i) \tag{A.1.5}$$

Solving each insurer's first order condition yields a system of n-equations:

$$\begin{bmatrix} a_n + b_n c_1(\vec{x}) \\ a_n + b_n c_2(\vec{x}) \\ \vdots \\ a_n + b_n c_n(\vec{x}) \end{bmatrix} = \begin{bmatrix} 2b_n & -z_n & \dots & -z_n \\ -z_n & 2b_n & \dots & -z_n \\ \vdots & \vdots & \ddots & \vdots \\ -z_n & -z_n & \dots & 2b_n \end{bmatrix} * \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_n \end{bmatrix}$$

I solve this system of equations numerically to yield the equilibrium premiums for each insurer as a function of all n insurers' investment decisions: $p_i^*(\vec{x})$.

Deriving the spillover effect on markup:
First, I take insurer i's first order condition from their choice of premium (given all other insurer's premiums and all insurers' investment choices) and solve for insurer i's optimal choice of premium:

$$\begin{aligned} \frac{\partial \pi_i}{\partial p_i} &= a_n + b_n * c_i(\vec{x}) - 2b_n p_i + z_n \sum_{j \neq i} p_j = 0 \\ p_i^* &= \frac{a_n}{2b_n} + \frac{c_i(\vec{x})}{2} + \frac{z_n}{2b_n} \sum_{j \neq i} p_j \end{aligned}$$

I differentiate insurer i's optimal choice of premium with respect to their own investment, x_i:

$$\frac{\partial p_i^*}{\partial x_i} = \frac{1}{2}\left(\frac{\partial c_i}{\partial x_i}\right) + \frac{z_n}{2b_n} \sum_{j \neq i} \frac{\partial p_j}{\partial x_i} \tag{A.1.6}$$

$$\frac{\partial (p_i^* - c_i)}{\partial x_i} = \left[\frac{1}{2}\left(\frac{\partial c_i}{\partial x_i}\right) + \frac{z_n}{2b_n} \sum_{j \neq i} \frac{\partial p_j}{\partial x_i}\right] - \frac{\partial c_i}{\partial x_i} \tag{A.1.7}$$

Note: for every insurer, their optimal choice of price depends on the investment from each other insurer and this effect is symmetric and constant for all insurers. Therefore, we can rewrite the above equation to remove the summation:

$$\frac{\partial (p_i^* - c_i)}{\partial x_i} = -\frac{1}{2}\left(\frac{\partial c_i}{\partial x_i}\right) + (n-1)\frac{z_n}{2b_n}\frac{\partial p_j}{\partial x_i} \tag{A.1.8}$$

Proof: The spillover effect on markup increases with the number of insurers (n)

From the previous equation, I plug in the demand parameters from Equation A.1.3:

$$\begin{aligned} \frac{\partial(p_i^* - c_i)}{\partial x_i} &= -\frac{1}{2}\left(\frac{\partial c_i}{\partial x_i}\right) + (n-1) * \frac{z_n}{2b_n} && \text{(A.1.9)} \\ &= -\frac{1}{2}\left(\frac{\partial c_i}{\partial x_i}\right) + \frac{(n-1) * \delta}{2(1 + (n-2) * \delta)} && \text{(A.1.10)} \end{aligned}$$

Differentiating with respect to n:

$$\frac{\partial^2(p_i^* - c_i)}{\partial x_i \, \partial n} = \frac{\delta * (1-\delta)}{(1 - \delta(n-2))^2} > 0 \quad \text{(A.1.11)}$$

Since $1 > \delta$ by assumption, the spillover effect is increasing in n.

Proof: The spillover effect on markup increases with competition (δ)

It follows from Equation A.1.8 that the spillover effect on markup will be increasing in δ if $z_n(\delta)$ is faster increasing in δ than $b_n(\delta)$. Differentiating $\frac{z_n}{b_n}$ with respect to δ:

$$\frac{1}{((n-2)\delta + 1)^2} > 0 \quad \text{(A.1.12)}$$

A.1.4 Solving for Optimal Insurer Investment

Using insurers premium decision rules, I can rewrite each insurer's profits as a function of all insurers' investments:

$$\pi_i(\vec{x}) \;=\; q_i(p_1^*(\vec{x}), ..., p_n^*(\vec{x})) * [p_i^*(\vec{x}) - c_i(\vec{x})] - V(x_i)] \tag{A.1.13}$$

$$\max_{x_i} \quad [a_n - b_n p_i^*(\vec{x}) + z_n \sum_{j \neq i} p_j^*(\vec{x})] * [p_i^*(\vec{x}) - c_i(\vec{x})] - V(x_i)] \tag{A.1.14}$$

Insurer i's optimal choice of investment is given by the first order condition:

$$x_i : \quad \left[\frac{\partial q_i}{\partial p_i^*}\frac{\partial p_i^*}{\partial x_i} + \sum_{j \neq i} \frac{\partial q_i}{\partial p_j^*}\frac{\partial p_j^*}{\partial x_i}\right] * [p_i^*(\vec{x}) - c_i(\vec{x})] \;+\; q_i(p_1^*(\vec{x}), ..., p_n^*(\vec{x})) * \left[\frac{\partial p_i^*}{\partial x_i} - \frac{\partial c_i}{\partial x_i}\right] \;-\; \frac{dV}{dx_i} \;=\; 0$$

Solving this system of n equations yields the symmetric nash equilibrium choices of investment for each insurer:

$$x_i^* \;= x^*(n, \delta; r_{CS}, r_{VB}, t, d, \nu, \alpha, \beta, \gamma) \quad \forall i \in \{1, ..., n\} \tag{A.1.15}$$

A.2 Data Appendix

A.2.1 OSHPD Discharge Data: Insurance Plan Information

The OSHPD discharge data contains plan codes identifying which plans patients list as their payers for patients enrolled in Knox-Keene licensed plans. In California, HMOs and PPOs are regulated by two separate agencies: HMOs are regulated by the Department of Managed Health Care under the Knox-Keene Act and PPOs are primarily regulated by the California Department of Insurance (Roth and Kelch, 2001). All HMOs must register as Knox-Keene plans. However, this also includes the Preferred Provider Organization (PPO) plans of Blue Cross and Blue Shield (Roth and Kelch, 2001). PPOs are a separate type of managed care plan. The main distinction is that HMO patients must receive authorization from a primary care provider to visit doctors in the HMO network, where PPO patients are allowed access to any provider in the network (Austin and Hungerford, 2009).

For simplicity, I use the term HMO to describe Knox-Keene plans from this point forward. More formally, by doing this I assume that all plans regulated by the California Department of Managed Health Care under the Knox-Keene act primarily compete with each other. The potential problem is that Blue Cross and Blue Shield PPOs are included in this category. To the degree that I cannot include the PPOs offered by the insurers who offer the other HMO plans this may overstate HMO concentration by overstating Blue Cross's and Blue Shield's hospital and market presence.

A.2.2 Medi-Cal HMOs

In order to fully explain how I calculate measures of insurer concentration, it is helpful to understand some background on the Medicaid system in California. Prior to 2013, Medicaid recipients in California had access to a Fee-For-Service (FFS) plan or HMO plan(s) depending on their county of residence. In California, patients eligible for Medi-Cal - the state run Medicaid Program - were allowed to opt into Medi-Cal HMOs in most counties. The type of HMO plan patients could enroll in, though, varied by county. Prior to 2013, there were three main types of Medi-Cal HMOs. First, in some counties, patients were only able to be enrolled in a County Organized Health System (COHS) operated by the county. Second, in other counties (2P) patients were allowed to opt into a plan supervised by the county (called a "local initiative") or a plan operated by a commercial insurer which contracts with the county. Third, there were two counties where multiple commercial insurers offered Medi-Cal HMO plans and patients can choose among them (Geographic Managed Care, GMC). In GMC counties, some of these plans are offered by commercial insurers that additionally serve private patients (i.e., Blue Cross). Other plans are operated by plans that only serve Medi-Cal patients. Among the counties that offered Medi-Cal HMOs, the important distinction was that in COHS counties, unlike the rest of the counties where Medi-Cal HMO plans are offered, the COHS plan does not compete against commercial insurers. Prior to 2013, the remaining counties only had access to a FFS plan. In 2013, though, while the existing types of Medi-Cal managed care counties remained the same, the state shifted the remaining FFS counties to a managed care model similar to the GMC counties (California Department of Health Care Services, 2014).

A.2.3 Variable Construction

To construct measures of HMO HHI at the hospital and market level, I first aggregate discharges to the plan level and calculate their share of HMO birth discharges at the hospital level and all discharges at the market level. To calculate HMO discharge totals at the hospital and market level (to eventually compute shares), I include Medi-Cal discharges from commercial HMOs and Medi-Cal HMOs that operate in Two Plan (2P) and Geographic Managed Care (GMC) counties. I omit Medi-Cal discharges from County Organized Health System (COHS) county plans because they do not compete with commercial insurers, as described above. For the commercial insurers offering Medi-Cal HMOs, I calculate each plan's discharge count at the hospital and market level as the sum of their Medi-Cal HMO discharges and private HMO discharges. To calculate HHI, I sum the squares of each plan share. Importantly, because of the overlap in the commercial and Medi-Cal HMOs market, in two plan, GMC and regional counties, I include Medi-Cal HMO plan shares when calculating HHI at both the hospital and market level. It is also worth noting that when calculating HHI, I include the share of Kaiser Permanente discharges at both the hospital and market level. The reason is that other HMOs still compete against Kaiser; I am only excluding Kaiser patients and hospitals from my sample.

In order to calculate market level HHI, I aggregate discharges by patients' market of residence as opposed to the market in which they receive treatment. For example, consider a patient who lives in Orange county and is treated at a hospital in Los Angeles (two different markets). To calculate market level HHI, I would include this discharge when aggregating discharges for Orange county. After computing market level HHI, I match each hospital to the market in which it lies thereby assigning a market level measure to each hospital.

For my instrumental variables, I use annual population estimates from the American Community Survey (ACS) for 2005-2013. I use each of the county level variables to create HRA-level population variables. I map each county that I observe to the relevant HRA. I create a HRA-level age demographic measures by taking the population-weighted average of counties within each HRA. Each county lies entirely within a single HRA with the exception of Los Angeles which is split into two HRAs. For each of these HRAs, I use the county level demographic measures.

A.2.4 Sample Construction

In my sample, I use observations where the patient is the mother and identify treatment and diagnoses using the Diagnosis Related Group (MS-DRG) codes and ICD-9 diagnostic and procedure codes. I omit observations with missing demographic, diagnostic, and insurance information in my baseline sample. I also omit patients who are from counties that do not have population estimates from the ACS. I further exclude patients in the 1$^{\text{st}}$ and 99$^{\text{th}}$ percentile of the age distribution, resulting in a sample of patients between the ages of 16 and 42.

I restrict my primary sample to mothers who are classified by the American College of Obstetrician-Gynecologists as lower risk for c-sections, following the methodology of Kozhimannil et al. (2013). Both my theoretical and empirical context relies on looking at a treatment where physicians have clinical flexibility to choose between an expensive treatment and a lower cost alternative. In the case of the decision to perform a C-section, in some cases this is more true than others. By restricting to lower risk pregnancies I am excluding pregnancies with ex-ante conditions identified by medical literature as predictive of receiving a C-section, and therefore looking at cases where physicians have more clinical flexibility. Following Kozhimannil et al. (2013), I define low risk pregnancies as full term, singleton pregnancies with vertex presentation and without a previous C-section. In addition to these conditions, I also exclude patients with history of diabetes or hypertension, following Foo et al. (2017). From this point forward, I define low risk births to additionally incorporate these restrictions.

I also restrict my baseline sample based on patients' hospitals and insurance plans. Similar to Kozhimannil et al. (2013), I exclude hospitals with fewer than 100 birth discharges in a calendar year. When defining sample hospitals by the volume of births, I count all birth discharges not just HMO patients. I exclude Kaiser Permanente hospitals from my sample, as discussed in Section 1.3.4. While I exclude Kaiser patients in my sample, Kaiser discharges are included in calculating market shares as other insurers still compete with Kaiser for potential clients. As discussed previously, I exclude patients from Medi-Cal HMOs in COHS counties. I also exclude patients from a small number of HMO plans which have limited licenses and others that have very few annual discharges.

A.3 Empirical Appendix

A.3.1 Falsification Test: Kaiser Hospitals

I argue that my use of instrumental variables allows for results that are not affected by the same endogeneity concerns as my OLS estimates. To provide evidence that my instrumental variables are not imposing results that are not otherwise found it is useful to check what happens when I use my instruments when estimating my baseline specification on a population that should exhibit no effect. For such a falsification test, I estimate my baseline specification on a sample of Kaiser Permanente patients at Kaiser Permanente hospitals.

As discussed in Section 1.3.4, Kaiser Permanente is an insurer that is vertically integrated with their hospitals; Kaiser hospitals exclusively contract with Kaiser Insurance (Ho, 2009).[1] Because Kaiser hospitals should not contract with other insurers, there should be no risk of spillover at these hospitals. Building off of the theoretical framework, if this is the case, insurer competition should not cause a distortion to Kaiser insurance's return on investing in cost reduction at Kaiser hospitals. In other words, competition should not affect whether Kaiser insurance decides to limit costly treatments. Therefore at these hospitals, there should be no effect of hospital level HHI on C-sections, nor should this effect vary with market level HHI.

The results of this test are presented in Table A.1, below. Hospital level HHI, market level HHI and their interaction do not have significant effects on C-section use at any acceptable statistical level in the specification estimated with OLS. Importantly, when I use the same instrumental variables for hospital and market level HHI and estimate the baseline specification with 2SLS, there is also no statistically significant effect of hospital level HHI, market level HHI, and their interaction on C-section use. This provides some evidence that my instrumental variables are imposing the results that I find in my main estimation.

[1] While Kaiser hospitals may only contract with Kaiser patients, it is inevitable that patients with other insurers end up at Kaiser hospitals. For this reason there is some intertemporal variation in insurer concentration at the hospital level for Kaiser hospitals.

Table A.1: Effect of Hospital and Market level Insurer HHI on C-Section Likelihood - Baseline versus Kaiser Hospitals

Sample:	Baseline		Kaiser Hospitals	
Estimator	OLS	2SLS	OLS	2SLS
Dependent Variable:	C-Section	C-Section	C-Section	C-Section
Variables:				
HHI, Hospital	-0.065***	-0.491***	0.076	0.215
	(0.016)	(0.144)	(0.074)	(0.318)
HHI, Market (HRA)	-0.003	-0.451***	0.502	-3.429
	(0.033)	(0.165)	(0.418)	(3.47)
HHI, Hospital x HHI, Market (HRA)	0.204***	1.497***	-0.565	3.356
	(0.064)	(0.554)	(0.423)	(3.522)
Hospital Controls	X	X	X	X
Labor Complication Controls	X	X	X	X
Patient Demographic Controls	X	X	X	X
Hospital, Insurer, Year FE	X	X	X	X
Number of Observations	736,403	736,403	332,432	332,423
Adj. R^2	0.302	0.302	0.372	0.367

Notes: All patient, insurer data is from the California OSHPD discharge data, 2005-2013. County and HRA population and age demographics are from the American Community Survey (ACS). Columns 3-4 are estimated using 2SLS. All control variables are defined as in Table 1.2. Standard errors are reported in parentheses; statistical significance denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All coefficients and standard errors are rounded to three digits.

Appendix B

Appendix to Chapter 3

B.1 Medicaid FFS vs. MMC Reimbursement Prices

Assumption 1: the reimbursement prices for C-section and Vaginal birth negotiated between the Medicaid HMO and contracted providers are set proportionally to some base rate. That is for each treatment τ, the negotiated reimbursement price ($p_\tau^{\text{neg.}}$) is some percentage (ϕ) of a base price(p_τ^{base}):

$$p_\tau^{\text{neg.}} \;=\; \phi * p_\tau^{\text{base}} \;,\; \phi > 0 \tag{B.1.1}$$

While it is possible that Medicaid HMOs could set reimbursement prices in some other fashion, Hunt et al. (2001) surveyed each of California's existing COHS plans, and found that each negotiated reimbursement prices as the percentage of some base rate. This is a common approach among private insurers (Clemens and Gottlieb, 2017; Foo et al., 2017).

Assumption 2: there is a difference between the base reimbursement prices for C-section and Vaginal births:

$$p_{CS}^{\text{base}} - p_{VB}^{\text{base}} \;>\; 0 \tag{B.1.2}$$

This assumption is valid if Medicaid HMOs use Medicare's reimbursement schedule as their base prices. Hunt et al. (2001) found that in 2001 the majority of the COHS plans essentially used Medicare's reimbursement prices as their base prices.[1] This is also a common approach among private insurers.[2] The other COHS plans surveyed by Hunt et al. (2001) use the Medicaid FFS prices as their base prices. If this is the case, assumption 2 is not valid.

Proposition 1: Conditional on assumptions 1 and 2, the switch from Medicaid FFS to a MMC will increase the difference between the reimbursement prices for C-sections and vaginal births. For simplicity, assume that the difference between the reimbursement prices for C-sections and vaginal births is zero for Medicaid FFS. Using assumptions 1 and 2, we can write the following expression for the difference in the reimbursement prices negotiated by the Medicaid HMO:

$$p_{CS}^{\text{neg.}} - p_{VB}^{\text{neg.}} = \phi * p_{CS}^{\text{base}} - \phi * p_{VB}^{\text{base}} \tag{B.1.3}$$

$$= \phi * (p_{CS}^{\text{base}} - p_{VB}^{\text{base}}) > 0 \tag{B.1.4}$$

Because there is no difference in the Medicaid FFS reimbursement prices, switching from FFS to a MMC will increase the difference in the prices for C-sections and vaginal births.

Proposition 2: Conditional on assumptions 1 and 2, the difference between the reimbursement prices for C-sections and vaginal births is increasing in the proportion from the base prices to the negotiated prices (ϕ). Rewriting the above equation (9.4):

$$p_{CS}^{\text{neg.}} - p_{VB}^{\text{neg.}} = \phi * (p_{CS}^{\text{base}} - p_{VB}^{\text{base}}) \tag{B.1.5}$$

[1] While some of the COHS plans explicitly set reimbursement prices as a percentage of the Medicare schedule others, for example, set their reimbursement prices as a percentage of the Medicaid FFS prices with a floor that is a percentage Medicare prices. Because the Medicaid prices are so low relative to the Medicare prices, the Medicaid prices - in the case of C-sections and Vaginal births - are generally below the floor prices; these COHS reimbursement rates are thus essentially set as a percentage of the Medicare rate.

[2] Clemens and Gottlieb (2017): insurers offer typically offer providers "contracts based on a fixed fee schedule. This may be Medicare's schedule of relative rates or a customized fee schedule. The parties then negotiate dollars-per-unit scaling, known as a conversion factor, which can itself be negotiated relative to Medicare's Conversion Factor." Foo et al (2017): "some insurers negotiate fees as a percentage of the Medicare fee schedule. [However, other] insurers use their own proprietary fee schedules in which the relative prices of services differ from relative prices on the Medicare fee schedule."

This implies:

$$\frac{\partial(p_{CS}^{\text{neg.}} - p_{VB}^{\text{neg.}})}{\partial\phi} \;=\; p_{CS}^{\text{base}} - p_{VB}^{\text{base}} \;>\; 0 \tag{B.1.6}$$

If the negotiated reimbursement prices between a Medicaid HMO and a provider are a larger percentage of the base rate, the difference between the negotiated reimbursement prices for C-sections and vaginal births will be larger.

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